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A Framework based on Load Monitoring and Association Rules Mining for Pattern Recognition in Smart Homes

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Abstract. This paper presents an integrated analytical framework for residential energy management that combines appliance-level load monitoring with behavioral pattern discovery using data from a unified smart home deployment. The research employs a two-phase methodology on synchronized datasets collected from the same residential environment. First, a Random Forest classifier is trained to identify individual household appliances from aggregate electrical measurements, achieving highly accurate classification performance for eight appliance types. Then, appliance activation records are analyzed within a given time window using Association Rule Mining, which reveals significant co-occurrence patterns. This framework presents how synchronized load monitoring, combined with data mining, can offer holistic information for optimizing energy consumption, demand response programs, as well as power quality assessment, especially in environments that incorporate renewable energy sources.

Keywords. Association Rule Mining, Load Monitoring, Machine Learning, Smart Home

1. Introduction

The transformation of residential buildings into smart energy systems necessitates advanced approaches that can decipher complex appliances consumption patterns while maintaining grid stability [1]. Modern smart homes, particularly those integrating renewable energy resources, require monitoring system that extends beyond aggregate consumption to appliance-level visibility and behavioral understanding [2]. A key challenge lies in developing methods that can accurately identify individual appliances from whole-home electrical data while also discovering meaningful usage patterns that emerge from their simultaneous operation.

Recent advances in machine learning (ML) have enabled significant progress in identifying electrical appliances from composite load signatures [3]. These approaches analyze features such as power consumption patterns, harmonic distortions, and transient events to distinguish between different device types. Concurrently, data mining techniques like Association Rule Mining have proven to be effective in discovering meaningful co-occurrence patterns in various applications [4]. However, limited number of researches have explored the integration of these approaches using synchronized data from the same residential environment, particularly for applications involving power quality assessment and renewable energy integration, where understanding appliance interactions is crucial [5].

This paper presents a unified framework that addresses this gap by analyzing synchronized data from a single smart home through two complementary perspectives. This integrated approach enables both precise appliance identification and discovery of behavioral relationships that can inform comprehensive energy management strategies. The main contributions of this work are: (1) development of a highly accurate classification model for appliance identification using comprehensive electrical features; (2) discovery of significant association rules from synchronized co-occurrence data; and (3) creation of a pipeline that connects detailed load monitoring with behavioral pattern for holistic smart home energy management with attention to power quality implications.

2. Dataset Description

This study utilizes synchronized datasets collected from a single residential deployment, providing complementary perspectives on appliance usage through two distinct analytical formats [6].

A. Time-Series Dataset for Appliance Classification

The classification dataset comprises 84,080 timestamped samples of aggregate electrical measurements captured at the home's main electrical panel. Each sample consists of 28 features that describe the composite load signature, with particular emphasis placed on those features that are relevant to energy monitoring and power quality analysis. These include:

- Fundamental Electrical Parameters: active power, reactive power, apparent power, current, voltage, phase angle
- Power Quality Parameters: harmonic delta components from 1 to 9, and transient state from 1 to 10

These features describe the electrical signatures of each appliance and also monitor the interaction between the grid and each appliance, which is essential for renewable energy integration. The target variable represents which of the eight most commonly used household appliances are active at any given time.

B. Transactional Dataset for Behavioral Pattern Mining

Derived from the same residential deployment, this dataset contains 28,903 transactions representing appliance co-occurrences over defined time windows. Each transaction lists all appliances active simultaneously during specific periods, creating a market-basket format ideal for association rule mining. Although this data is derived from the same source as the classification data, it has been designed independently with the aim of detecting behavioral patterns rather than electrical activity, thereby allowing the detection of relationships between habits.

The synchronization between these datasets ensures that discovered association rules correspond to genuine usage patterns in the monitored environment, while the classification model provides the granular appliance identification necessary for accurate pattern analysis.

3. Machine Learning Approach and Performance Metrics

This section outlines the ML approach employed for the precise identification of electrical appliances and details the metrics used to evaluate model performance.

A. Machine Learning Approach

To address the challenge of appliance identification from aggregate electrical data, a Random Forest Classifier was implemented. Random Forest is an ensemble learning method that works by creating a large number of decision trees and returning the most frequently predicted class for classification problems [7]. The algorithm was chosen because of its effectiveness with complex and high-dimensional problems with non-linear relationships, which is characteristic of electrical load signature data [8].

The ensemble nature of the Random Forest approach avoids the overfitting problem associated with individual decision trees by the process of bootstrap aggregation (bagging), as well as random feature selection. Additionally, it allows for an estimate of feature importance. This can provide significant insight into which particular electrical characteristics (such as specific types of harmonic distortions or values of reactive power) are most important for distinguishing between different appliances [9]. This interpretability of the results is in line with well-known principles of electricity and can be considered trustworthy.

***B.** Performance Metrics*

The performance of the multi-label classification model was rigorously tested using a set of standard metrics, each of which offered a different viewpoint on the accuracy of the model. Accuracy is the measure of the overall proportion of correct predictions for all classes of appliances [10], and it is given by (1). Precision (Positive Predictive Value) is a measure of the model's capability to prevent false alarms in predicting an appliance is active [10], given by (2). Recall (Sensitivity) is a measure of the model's capability to detect all instances of an active appliance [10], presented by (3). The F1-Score is a balanced measure that is the harmonic mean of Precision and Recall [10], given by (4). Finally, Hamming Loss, which is a specialized measure for multi-label classification, calculates the proportion of incorrectly labeled predictions to the total number of labels [11], given by (5), where a lower value is a measure of better performance.

The abbreviations and variables in equations (1) to (5) are described as follows: TP, TN, FP and FN stand for: True Positive, True Negative, False Positive and

False Negative respectively, N is the total number of samples, L is the number of labels (appliances), y_{ij} is the true label, and $\hat{y}_{ij}$ is the predicted label for the i-th sample and j-th label.

$$Accuracy = \frac{\text{TP} + \text{TN}}{TP + FN + TN + FP} \quad (1)$$

$$Precision = \frac{\text{TP}}{TP + FP} \quad (2)$$

$$Recall = \frac{\text{TP}}{TP + FN} \quad (3)$$

$$F1 - score = 2 \times \frac{\text{Precision} \times \text{Recall}}{Precision + Recall} \quad (4)$$

$$Hamming\ Loss = \frac{1}{N.L}\sum_{i=1}^{N}\sum_{j=1}^{L} 1(y_{ij} \neq \hat{y}_{ij}) \quad (5)$$

4. Association Rule Mining

To identify significant co-occurrence patterns of household appliances, Association Rule Mining (ARM) was employed for the transactional set of data. ARM is an established data mining method for identifying interesting relationships among variables in large databases [12]. In this case, an association rule is represented as $X \rightarrow Y$, where X, the antecedent, and Y, the consequent, are disjoint sets of household appliances. This indicates that the set of transactions containing itemset X tends to include itemset Y.

A. Algorithm: Apriori

The Apriori algorithm was used for rule generation because of its efficiency and popularity for mining frequent itemsets [13]. It works on the basis that any subset of a frequent itemset is also frequent (downward closure property). The algorithm uses an iterative, breadth-first search approach, as follows [13]:

1) *Candidate Generation:* Frequent itemsets of size k are used as input for candidate generation for size $k+1$.

2*) Support Pruning:* The support value of each candidate is determined by scanning the transactional database. Candidates not satisfying a minimum support requirement are pruned.

3) *Rule Generation:* Association rules are derived from the last set of frequent itemsets. All possible binary splits of a frequent itemset are examined as candidate rules $X \rightarrow Y$, if they satisfy a minimum confidence requirement.

B. Rule Evaluation Metrics

The strength and significance of the discovered rules were evaluated using three fundamental metrics: *support*, *confidence*, and *lift*.

The support of a rule $X \rightarrow Y$ measures its overall frequency within the dataset, representing the proportion of transactions that contain both the antecedent and consequent itemsets [14], as defined in (6). The confidence quantifies the rule's reliability or conditional probability, indicating how often itemset Y appears in transactions that contain X [15], following (7). While support and confidence are essential for filtering prevalent and reliable rules, lift assesses the degree of statistical dependence between the antecedent and consequent. It calculates the ratio of the observed co-occurrence frequency and the expected frequency when X and Y are independent, as shown in (8). A lift value higher than 1 signifies a positive dependence, meaning that the occurrence of X enhances the occurrence of Y. A value lower than 1 signifies a negative dependence, while a value of 1 signifies statistical independence between the two itemsets [16]. In this study, rules exhibiting high support, confidence, and lift (>1) are considered strong and actionable patterns for understanding habitual appliance usage behavior.

In these equations, frq(X,Y) denotes the number of transactions containing both itemsets X and Y, frq(X) is the number of transactions containing itemset X, and N is the total number of transactions in the dataset. $P(A \cup B)$ is the probability of X and Y occurring together, while P(X) and P(Y) are the individual probabilities of X and Y, respectively.

$$support = \frac{frq(X,Y)}{N} \quad (6)$$

$$Confidence = \frac{frq(X,Y)}{frq(X)} \quad (7)$$

$$Lift = \frac{P(A \cup B)}{P(A)\, P(B)} \quad (8)$$

5. Methodology

This section details the systematic, multi-stage, analytical pipeline employed in this study.

A. Data Preparation

Two synchronized datasets from a single residential deployment were utilized. The appliance identification dataset has 84,080 timestamped aggregate electrical measurements. To ensure data integrity and model robustness, a series of preprocessing operations were performed. These operations involved dealing with missing data, eliminating duplicates, normalizing data formats, and detecting statistical outliers. In addition, all numerical data was normalized to a range of [0, 1] via min-max scaling. This preprocessing mitigates the influence of differing feature scales and promotes stable model convergence [17]. The ARM dataset, containing 28,903 transactions of appliance co-occurrences, required minimal preprocessing, primarily involving the verification of transaction format consistency.

B. Model Development and Evaluation for Appliance Identification

A Random Forest classifier was implemented for the multi-label classification task of identifying active appliances from the aggregated electrical signature. The classification dataset was partitioned using a hold-out strategy: 80% for model development and 20% as a hold-out test set for final evaluation. The development set was further split into a training subset (60% of the total data) and a validation subset (20% of the total data) used for hyperparameter tuning. Key hyperparameters for the Random Forest, such as the number of trees and maximum depth, were optimized via grid search on the validation set. The model was evaluated on the unseen test set using the comprehensive suite of metrics defined in Section 3.B (Accuracy, Precision, Recall, F1-Score, Hamming Loss), with their corresponding equations (1) to (5).

C. Association Rule Mining and Pattern Discovery

The transactional data of appliance co-occurrences was then mined using the Apriori algorithm to identify the significant association rules of the form $X \rightarrow Y$. The Apriori algorithm was set to have a minimum support of 10% and a minimum confidence of 10% to identify rules that are both frequent and accurate. The identified rules were then analyzed and prioritized based on the support, confidence, and lift measures, as formally defined in (6) to (8) The lift measure was particularly important in identifying rules that indicate significant positive dependencies (lift>1) in appliance usage behavior.

D. Integrated Analysis and Interpretation

The final phase is the synthesis and combined interpretation of the results of both analytical streams. The accurate predictions of the classification task enable the granular appliance-level load monitoring. At the same time, the high-level association rules enable a higher-level interpretation of the behavioral patterns. This combined view enables a holistic analysis of residential energy use, connecting specific electrical events (such as harmonic distortion caused by a microwave) to higher-level behavioral patterns (such as its co-occurrence with a kettle), thus enabling a multi-faceted analysis for energy and power quality.

6. Results

This section presents the outcomes of the two parallel analytical streams conducted in this study: the performance evaluation of the appliance classification model and the discovery of behavioral patterns

Table I. - Evaluation metrics values

	Accuracy	Precision	Recall	F1-score	Hamming loss
Fridge	100	100	100	100	0
Kettle	100	100	100	100	0
Microwave	100	100	100	100	0
Shower	100	100	100	100	0
Tumble Dryer	100	100	100	100	0
Vacuum	100	100	100	100	0
Washer Dryer	100	100	100	100	0
Washing machine	100	100	100	100	0

through association rule mining. The results from each stream are presented independently and subsequently synthesized in the Discussion section to provide integrated insights.

A. Appliance Classification Performance

The Random Forest classifier was evaluated on the held-out test set comprising 20% of the classification dataset. The model's performance across all eight appliance categories is summarized in Table I. The classifier performed with perfect accuracy, precision, recall, and F1-score of 100%, and a Hamming Loss of 0% for all appliances, meaning that it performed flawlessly on the test data.

B. Discovered Association Rules from Behavioral Data

Applying the Apriori algorithm with a minimum support of 10% and minimum confidence of 10% to the independent transactional dataset yielded 62 strong association rules. A selected subset of these rules, highlighting the most significant patterns, is presented in Table II. The complete set of rules demonstrates diverse co-occurrence relationships between appliances, derived directly from observed usage behavior. The most frequent rule, with 59% support, is the bidirectional rule between fridge and washer_dryer (Rules #11, #12), showing their most popular co-occurrence in the household context. The most statistically significant rule is tumble_dryer → washer_dryer (Rule #21), showing the strongest association with the highest lift of 1.50591 and 100% confidence, showing a very strong positive association between the two appliances used for laundry. Other significant rules with 100% confidence are microwave → fridge (Rule #3) and vacuum → fridge (Rule #9), showing that the fridge is used as a background task while performing other tasks at home. The lift of some of the rules is less than 1, showing a negative dependence where these appliances are less likely to co-occur than if they were independent, such as washer_dryer → kettle (Rule #15, lift=0.749).

Table II. - Selected association rules with support (S), confidence (C) and lift values

No.	Association Rules			S (%)	C (%)	Lift	No.	Association Rules			S (%)	C (%)	Lift
1	fridge	→	kettle	25	30	1.02845	**32**	fridge, kettle	→	washer_dryer	14	56	0.74934
2	kettle	→	fridge	25	87	1.02845	**33**	washer_dryer	→	fridge, microwave	14	21	0.99418
3	microwave	→	fridge	22	100	1.17406	**34**	microwave	→	fridge, washer_dryer	14	66	1.11848
4	fridge	→	microwave	22	25	1.17406	**35**	fridge	→	microwave, washer_dryer	14	17	1.17406
5	shower	→	fridge	18	83	0.97498	**36**	fridge, washer_dryer	→	microwave	14	24	1.11848
6	fridge	→	shower	18	21	0.97498	**37**	fridge, microwave	→	washer_dryer	14	66	0.99418
7	tumble_dryer	→	fridge	22	85	1.00264	**38**	microwave, washer_dryer	→	fridge	14	100	1.17406
8	fridge	→	tumble_dryer	22	25	1.00264	**39**	washer_dryer	→	fridge, shower	11	16	0.89797
9	vacuum	→	fridge	14	100	1.17406	**40**	shower	→	fridge, washer_dryer	11	49	0.83895
10	fridge	→	vacuum	14	17	1.17406	**41**	fridge	→	shower, washer_dryer	11	12	1.17406
11	washer_dryer	→	fridge	59	88	1.04358	**42**	fridge, shower	→	washer_dryer	11	59	0.89797
12	fridge	→	washer_dryer	59	69	1.04358	**43**	shower, washer_dryer	→	fridge	11	100	1.17406
13	fridge	→	washing_machine	18	22	1.17406	**44**	fridge, washer_dryer	→	shower	11	18	0.83895
14	washing_machine	→	fridge	18	100	1.17406	**45**	tumble_dryer	→	fridge, washer_dryer	22	85	0.72239
15	washer_dryer	→	kettle	14	22	0.74934	**46**	washer_dryer	→	fridge, tumble_dryer	22	33	0.56432
16	kettle	→	washer_dryer	14	49	0.74934	**47**	fridge	→	tumble_dryer, washer_dryer	22	25	1.00264
17	washer_dryer	→	microwave	14	21	0.99418	**48**	fridge, tumble_dryer	→	washer_dryer	22	100	1.50591
18	microwave	→	washer_dryer	14	66	0.99418	**49**	fridge, washer_dryer	→	tumble_dryer	22	37	1.44683
19	washer_dryer	→	shower	11	16	0.74571	**50**	tumble_dryer, washer_dryer	→	fridge	22	85	1.00264
20	shower	→	washer_dryer	11	49	0.74571	**51**	washer_dryer	→	fridge, vacuum	11	17	1.14375
21	tumble_dryer	→	washer_dryer	25	100	1.50591	**52**	vacuum	→	fridge, washer_dryer	11	75	1.28675
22	washer_dryer	→	tumble_dryer	25	39	1.50591	**53**	fridge	→	vacuum, washer_dryer	11	13	1.17406
23	washer_dryer	→	vacuum	11	17	1.14375	**54**	fridge, washer_dryer	→	vacuum	11	19	1.28675
24	vacuum	→	washer_dryer	11	75	1.14375	**55**	vacuum, washer_dryer	→	fridge	11	100	1.17406
25	washer_dryer	→	washing_machine	18	28	1.50591	**56**	fridge, vacuum	→	washer_dryer	11	75	1.14375
26	washing_machine	→	washer_dryer	18	100	1.50591	**57**	washer_dryer	→	fridge, washing_machine	18	28	1.50591
27	washer_dryer	→	fridge, kettle	14	22	0.85543	**58**	fridge	→	washer_dryer, washing_machine	18	22	1.17406
28	fridge	→	kettle, washer_dryer	14	17	1.17406	**59**	washing_machine	→	fridge, washer_dryer	18	100	1.69419
29	kettle	→	fridge, washer_dryer	14	49	0.84303	**60**	fridge, washer_dryer	→	washing_machine	18	31	1.69419
30	kettle, washer_dryer	→	fridge	14	100	1.17406	**61**	washer_dryer, washing_machine	→	fridge	18	100	1.17406
31	fridge, washer_dryer	→	kettle	14	24	0.84303	**62**	fridge, washing_machine	→	washer_dryer	18	100	1.50591

7. Discussion and Future Works

The results show the efficacy of the suggested framework, where the Random Forest classifier successfully identifies the appliances with perfect accuracy and ARM showing strong behavioral patterns such as the significant co-occurrence of the appliances tumble_dryer and washer_dryer. This validates the idea that by accurately monitoring the loads and analyzing the usage patterns, a more holistic approach is achieved for the study of the dynamics of the energy usage in a residential environment, which is useful for load forecasting and power quality management by relating the appliances' combinations with the harmonic distortions or peaks. For further research, it is important to study the impact of the change of seasons and climatic conditions. Also, by studying more appliances and devices in the smart home ecosystem, more complex relationships can be established for the holistic approach.

8. Conclusions

This paper presented an integrated framework for smart home energy management, combining high-accuracy appliance identification with behavioral pattern discovery. A Random Forest classifier was successfully employed for load monitoring, achieving perfect performance metrics (100% accuracy, precision, recall, F1-score) in identifying eight common household appliances from aggregate electrical measurements, thereby establishing a reliable method for fine-grained, non-intrusive load disaggregation. In parallel, ARM applied to independent co-occurrence data uncovered strong and interpretable usage patterns, highlighting significant habitual dependencies between devices.

The main contribution of this research is the illustration of how these two methods, the precise classification of electrical events and behavioral habit mining, complement each other in providing a multi-dimensional view of electrical consumption. Such synergy has practical applications in the optimization of demand side management, predictive maintenance, and localized power quality assessment of specific combinations of electrical devices. This research created a foundation that can guide further researches in exploring the temporal characteristics of the patterns, such as seasonal and daily changes, and expanding the scope of devices under investigation, contributing to more adaptive and efficient smart home systems with renewable energy integration.

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