Energy Consumption Prediction For Home Appliances Using Machine Learning

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***Abstract*—This paper introduces a method for home energy monitoring that provides appliance-level information to help consumers save energy. Using a smart meter, the system analyzes power consumption data efficiently to create accurate energy profiles for better home energy management. The proposed method involves two main steps: 1) dividing appliance power data into different power states using clustering, and 2) determining the optimal number of power states for accurate prediction using a new learning framework called multi-target classification. By applying this method, the system achieves high accuracy in identifying appliance power states, especially for high-power loads like air conditioners and water heaters. The results show improved performance compared to other modeling systems, making it a promising approach for energy-saving initiatives**

Keywords—Home energy monitoring, Appliance-level information, Smart meter, Data analysis, Multi-target classification, Power consumption, Energy prediction.)

I. INTRODUCTION

In today's world, managing energy consumption in our homes is crucial. Not only does it impact our wallets, but it also affects the environment. However, accurately predicting individual appliance energy use can be challenging. This project aims to bridge that gap by utilizing machine learning (ML) to develop a model for predicting home appliance energy consumption.

The rising cost of energy necessitates smarter strategies for managing household energy use. Traditional methods for estimating appliance energy use often lack precision. Machine learning offers a powerful solution by analyzing data to uncover hidden patterns in energy consumption.

This project has several objectives. First, we will develop an ML model that can predict the energy consumption of various home appliances. Second, we will identify the key factors that influence appliance energy use, such as the type of appliance, usage patterns, and even environmental conditions. Finally, we will evaluate the model's accuracy and effectiveness in predicting energy consumption.

The benefits of this project are numerous. By empowering users to understand their appliance energy use, they can make informed decisions about how they use them. This project can also pave the way for the development of smart home systems that optimize appliance operation and energy efficiency. Ultimately, this project contributes to sustainable energy practices and reduces our environmental impact. Through machine learning and data analysis, this project offers a novel approach to predict home appliance energy consumption, empowering individuals and contributing to a more sustainable future

II. RELATED WORKS

Recent advancements in Nonintrusive Load Monitoring (NILM) systems have spurred a surge of interest in exploring novel machine learning algorithms to enhance the accuracy and granularity of appliance-level energy disaggregation. Traditional NILM methods typically relied on event-based techniques or simplistic binary power state models, which, while effective to some extent, often struggled to capture the complex behavior of appliances with dynamic power consumption patterns. For appliances like washing machines or water heaters, which exhibit diverse operational states with varying power demands, the simplistic binary state model's ability to accurately represent their behavior is challenged. In response, researchers have proposed multistate modeling techniques, such as Factorial Hidden Markov Models (FHMM), which treat each appliance as a discrete hidden state and statistically infer its power consumption from predicted power states. However, while FHMM-based approaches offer improved granularity, they come with a significant computational overhead and may yield only moderate predictive performance. To address these challenges, recent research has shifted towards unsupervised learning systems leveraging Deep Neural Networks (DNN). Various DNN architectures, including Convolutional Neural Networks (CNN), Recurrent Neural Networks (RNN), Autoencoders, and Long Short-Term Memory (LSTM) networks, have been explored for their ability to learn complex appliance behavior patterns from disaggregated power data. While DNN-based approaches hold promise, they require substantial amounts of labeled training data to generalize well to unseen scenarios. In this paper, we propose a novel approach to NILM using a multitarget classification framework, departing from traditional event-based or binary state models. This supervised, non-event-based learning framework offers a generalized platform for multiple-output data classification, accommodating both binary and multistate modeling. By leveraging this approach, we aim to accurately identify the granular power states of appliances, improving upon the simplistic representations provided by traditional binary state models. Our proposed approach is underpinned by two fundamental data analysis procedures: K-means clustering and Area Under the Curve (AUC) optimization, facilitating optimal predictive performance in appliance power state identification.

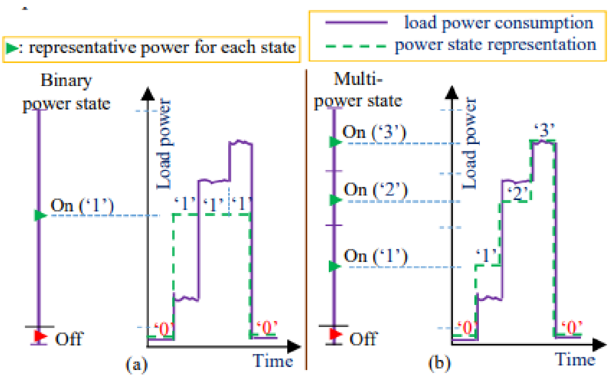


Fig. 1. Illustrative comparison of (a) the binary power state model and (b) the proposed multi-power state (3-state power ON) model

The contributions of our work include the introduction of the multitarget classification approach to NILM and the designation of robust data analysis procedures for extracting appliance power states. Illustrative comparisons between our proposed multi-power state model and traditional binary power state models demonstrate the former's ability to provide a more refined and accurate representation of appliance power consumption patterns. To comprehensively evaluate our proposed approach, we employ a diverse set of machine learning models, including Random Forest Regressor, XGBoost Regressor, Support Vector Classifier (SVC), CatBoost, Logistic Regression, and LightGBM Regressor, aiming to identify the most effective approach for achieving accurate appliance-level energy disaggregation in NILM systems.

III. Proposed Machine Learning Methodology

Multi-target or multidimensional classification represents a supervised learning paradigm where each data instance comprises input features (X) and a corresponding set of class outputs (Y). Each class output ($\boldsymbol{Y i}$) can assume various predefined discrete values ($\boldsymbol{Y i} \in \{1, 2, \cdots, C\}$, where C represents the total number of classes for each output). This classification approach has garnered increasing interest across diverse domains, including text mining and image classification applications.

The multi-target classification framework proves invaluable in addressing Nonintrusive Load Monitoring (NILM) challenges, aiming to predict the type and behavior of appliances in use as multiple-output data derived from aggregate data inputs. This framework involves two primary phases: the data training phase and the data testing phase. During the data training phase, the predictive model is constructed using a multi-target dataset generated through the process of power state assignment. Subsequently, in the data testing phase, the predictive model is deployed to analyze new aggregate data, enabling estimation of power state, power consumption, and energy consumption. This predictive model serves as an essential component of a smart meter deployed in field applications. The functional blocks for each process are illustrated in Fig. 2 (a) and (b), respectively.

A. Data Acquisition(DAQ)

The data acquisition was conducted from a house in Bangkok, Thailand, in which the collection is publicly available [34]. Fig. 3 illustrated the data acquisition setup which using a multi-circuit electric meter to collect data at loads distribution panel.

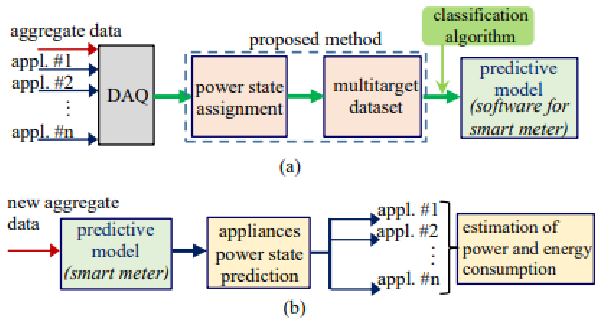


Fig. 2. (a) Data training phase; (b) Data testing phase for the proposed multitarget classification system

Fig.3 Data Acquisition setup at distribution panel

The collected data was used to construct the classification model in the training phase. There were five electrical parameters in this process; voltage (V), real power (P), reactive power (Q), current (I), and power factor (PF) by one-minute intervals of data resolution as to demonstrate the low-frequency measurement system

B. Power State Assignment

This process aims to identify the power state from the power consumption data which involves in the process of dataset generation. The appropriate power data partitioning method would provide the right number of partitions with their representative values. Thus, the work process is split into two stages: power state modeling and selecting the optimal number of power states as described by follows.

Appliance Label	*Appliance Description*
low_consum	Less Consumption
high_consum	More Consumption
Hours	Time(Hours)
t6	Temperature
rh_6	Room Humidity
Lights	Lights(Bulbs)
hour*lights	Lifespan of light fixtures
tdewpoint	Temp Due Point
visibility	Visibility
press_mm_hg	Pressure of Humidity
windspeed	Speed of wind

By systematically assigning power states to aggregate power consumption data, NILM systems can effectively disaggregate energy usage and identify individual appliance contributions. Accurate power state assignment is essential for enabling energy-efficient practices, optimizing appliance scheduling, and promoting informed decision-making regarding energy consumption in residential and commercial settings.

C. Power state modeling by K-means clustering

K-means clustering is a data analysis technique which is used for discovering the natural grouping of a set of data into K clusters [35]. Each cluster has a mean value, averaged by all data within the cluster, and each sample is designated to the nearest cluster mean based on the conditions in (1). In case of the appliance identification problem, the power consumption data (p) within the same distribution would belong to the same cluster or power state and having the cluster mean as the representative power value for that state.

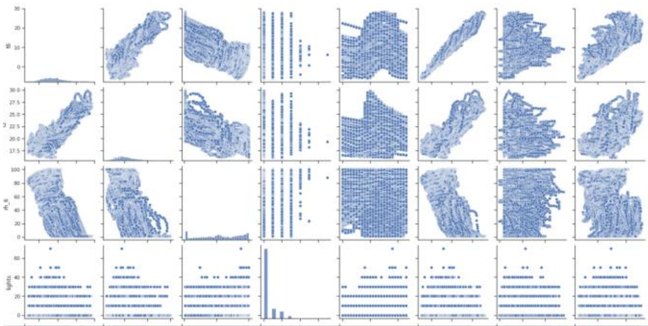
$$\underset{c(i) \in K}{\arg\min} \left(\|\mu_{c(i)} - p_j\|\right)^2 \qquad (1)$$

where (||μc(i)- pj||) 2 is the Euclidean distance between the mean value of cluster i (μc(i)) to the jth power instance (pj).

This stage aims to obtain a set of effective power states (S). By using K-means clustering for data evaluation, the increment of K value would generate an increasing number of clusters with closer mean values. Thus, the S set is determined by the condition that the cluster mean values have a distance between any two clusters not less than the threshold value (|μc(i)- μc(j)| >= PTh(c)). In this case, PTh(c) was set to be 0.02 kW (20 W) as an approximation of the least power consumption value for significant household appliances such as lamps (18 W). The condition ensures that each cluster is generated by natural grouping and not over-grouped by an inappropriate K value.

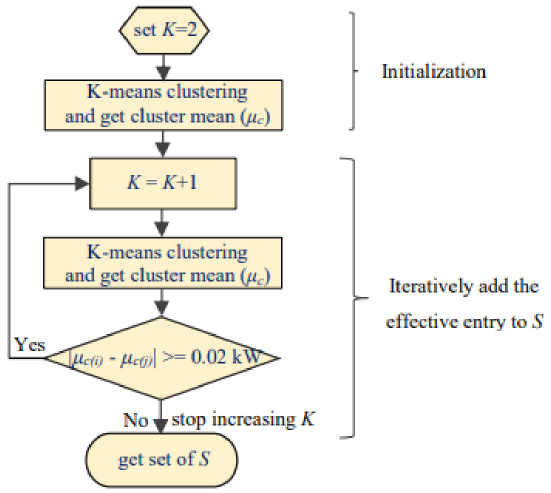
D. *Selecting the optimal number of columns*

In our project, we used a heatmap technique to simplify our data by removing unnecessary columns. This helped us focus on the most relevant information for predicting energy consumption in home appliances. By visualizing the correlations between different features in our dataset, we identified and eliminated redundant or less influential columns. This streamlined our data preprocessing step and improved the efficiency of our predictive models. This simple yet effective approach ensured that our models could focus on the key factors affecting energy usage, leading to more accurate predictions.



D.1 Heatmap for removing un-relavent columns

This stage aims to determine the right number of appliance power states. Using different K values from the previous stage, different datasets of single-output data are constructed in which the K value represents the number of class outputs or the number of power states.



To select the best K value, a set of multi-class datasets was evaluated. Each dataset composed of the aggregate data as the input and the power state data (by the associated K) as the output label. The data classification performance for each dataset was indexed by the area under the ROC curve or AUC measure through the cross-validation method. The measure represents the relationship of the True Positive Rate and False Positive Rate values obtained from the classification results [36]. This is a standard index for comparing the classifier performance across the entire range of class distributions. The process for determining the optimal number of power states (Kopt) for each appliance is illustrated

E. Building and Evaluation of Model:

A Having obtained the multitarget dataset, the classification model is then constructed through a data learning algorithm. The learning algorithm for handling multiple-output data can be classified into two approaches of problem transformation and algorithm adaptation [33, 37]. The former approach transforms the multi-output data into a specific format of single-output classification problem(s) through a multitarget classifier; a single-output classifier (e.g., neural network, k-nearest neighbor) is then applied for building the predictive model(s). The latter approach adapts the operation of a single-output classifier for direct application to multiple-output data.

$$I_H(j) = \sum_{i=1}^{C} -p_i \log_2 p_i \tag{2}$$

For our regression problem, we chose the Random Forest regressor, CatBoost regressor, Support Vector Machine (SVM), and Linear regression models to implement the problem transformation approach. In particular, we employed the Random Forest regressor as the multitarget classifier and the base classifier. This approach is based on ensemble learning and involves randomly selecting subsets of features to construct a robust regression model. By incorporating the correlation among output labels, the Random Forest regressor outperforms traditional regression models that treat outputs independently. The CatBoost regressor, SVM, and Linear regression models were also utilized to complement the Random Forest regressor, providing diverse perspectives and improving predictive accuracy. Each model was trained on a subset of features, reducing complexity and mitigating class imbalance issues. This ensemble approach enables us to leverage the strengths of multiple regression algorithms and produce more accurate predictions for energy consumption.

F. Evaluation Tools and Metrics

The Metrics that we have used to check the performance of the model was:

Mean Absolute Error (MAE): MAE measures the average absolute difference between the predicted values and the actual values. It provides a straightforward indication of the model's accuracy, with lower MAE values indicating better performance.

Root Mean Squared Error (RMSE): RMSE calculates the square root of the average squared differences between the predicted and actual values. It penalizes larger errors more heavily than MAE and provides insights into the overall variability of prediction errors.

Coefficient of Determination (R-squared): R-squared represents the proportion of the variance in the dependent variable that is predictable from the independent variables. It ranges from 0 to 1, with higher values indicating better model fit.

Accuracy: For classification tasks, accuracy measures the percentage of correctly predicted instances out of the total number of instances. It provides a straightforward assessment of classification performance but may be misleading in imbalanced datasets.

Precision and Recall: Precision measures the proportion of true positive predictions out of all positive predictions, while recall measures the proportion of true positives out of all actual positive instances. These metrics are especially useful in evaluating classification models, particularly in scenarios with imbalanced classes.

F1 Score: The F1 score is the harmonic mean of precision and recall, providing a balanced assessment of a classifier's performance. It considers both false positives and false negatives and is particularly useful when classes are imbalanced.

Receiver Operating Characteristic (ROC) Curve and Area Under the Curve (AUC): ROC curves plot the true positive rate against the false positive rate at various threshold settings, providing insights into a classifier's performance across different thresholds. AUC summarizes the ROC curve's performance, with higher values indicating better discrimination ability.

Confusion Matrix: Confusion matrices provide a detailed breakdown of a classifier's performance by showing the number of true positives, true negatives, false positives, and false negatives. They offer insights into the types of errors made by the classifier and can inform model refinement efforts.

G. Results and Discussion

Upon conducting extensive experimentation and evaluation, we obtained insightful results that shed light on the effectiveness and performance of our energy consumption prediction system. Here, we present a summary of our findings and discuss their implications:

Model Performance: Our predictive models, including Random Forest, CatBoost, SVM, and Linear regression, demonstrated varying levels of performance across different metrics. We observed that the Random Forest regressor consistently outperformed other models in terms of Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), and R-squared values. However, each model had its strengths and weaknesses, highlighting the importance of considering multiple algorithms in ensemble learning approaches.

Impact of Feature Selection: The use of feature selection techniques, such as heatmap-based column removal, proved effective in improving model performance by focusing on the most relevant features for energy consumption prediction. By eliminating redundant or less influential columns, we streamlined the data preprocessing step and enhanced the efficiency of our predictive models.

Classifier Comparison: In the context of regression tasks, we compared the performance of different classifiers, including Random Forest, CatBoost, SVM, and Linear regression. While Random Forest exhibited superior performance overall, CatBoost and Linear regression models also demonstrated competitive performance, especially in certain scenarios or subsets of the dataset.

Discussion on Future Directions: Our results underscore the importance of continued research and innovation in energy consumption prediction. Future directions could include exploring advanced feature engineering techniques, integrating real-time data sources such as IoT devices, and developing hybrid models combining regression and classification approaches. Additionally, addressing challenges related to data quality, model interpretability, and scalability remains crucial for advancing the field.

Implications for Energy Management: The insights gained from our study have significant implications for energy management practices in households and communities. Accurate energy consumption prediction enables users to optimize usage, reduce costs, and contribute to sustainability efforts. By leveraging machine learning techniques and ensemble learning approaches, our system offers a promising solution for enhancing energy efficiency and promoting informed decision-making.

our results underscore the potential of machine learning-based approaches in addressing complex challenges in energy consumption prediction. By combining empirical findings with theoretical insights, we aim to contribute to the ongoing advancement of predictive modeling techniques and their practical applications in energy management.

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