Non-Intrusive Load Identification of Residential Appliances Using Improved Dictionary Learning Technique

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Abstract— **With the advent of time, the demand for power in the residential sector is increasing. Along with supply-side management, the demand side is also used to balance electricity and supply demand. To apply different demand-side management techniques, the energy disaggregation on metered data is used to retrieve information related to available demand. Non-intrusive load monitoring is a technique that separates the total power consumption into appliance loads with minimum invasion of privacy. Non-intrusive load monitoring covers the methods of Stochastic finite state machines, Neural Networks and Sparse Coding. Developing an efficient algorithm for NILM is a key challenge in maximizing energy conservation. Recently, a new deep learning technique called dictionary learning has been developed for energy disaggregation. Smart meters provide the whole house data, and the Dictionary technique is trained to predict an appliance's power or ON/OFF based on its power consumption. This research proposes the event-based dictionary learning technique, which can disaggregate multiple appliances through orthogonal matching pursuit (OMP) and kernel-singular value decomposition (K-SVD). The sparse matrix is predicted through OMP, and K-SVD predicts the dictionary matrix. The training, testing and validation are done on the ECO dataset. The results of this research are noticeable and show the validity of the proposed methodology for energy disaggregation.**

Index Terms— **Dictionary learning, non-intrusive load monitoring, residential load, sparse representation.**

I. INTRODUCTION

The residential and commercial areas consume almost 80% of the world's power [1]. This demand will increase shortly, so demand-side management is very important to tackle this situation. Residential demand is a pivotal factor in attaining equilibrium between energy supply and demand. It serves as a cornerstone for grid stability and efficiency. When residents actively manage their energy consumption, they assist in diminishing demand peaks, thus fostering a more stable grid. The overall efficiency of the energy system is enhanced. Demand-side management initiatives are crucial as they empower residents to partake in creating a sustainable energy future. By promoting energy efficiency and conservation, these initiatives reduce the strain on the grid and contribute to environmental conservation. Utilities benefit significantly from understanding and responding to residential demand patterns, allowing them to optimize their operations. Through this optimization, utilities can ensure a reliable energy supply for all customers, enhancing the overall resilience and sustainability of the energy ecosystem.

Effective and efficient methods are required to be implemented for demand-side management. Demand-side management includes the real-time monitoring and prediction of the appliances. To provide insight into power consumption, making the wastage powerless.

Real-time monitoring includes non-intrusive load monitoring (NILM) and Intrusive load monitoring (ILM). The installation of sensors is required for the appliances, which provide details about the appliance consumption at a specific time interval, but it is a costly and complex solution. The complexity of ILM allows us to find some alternative techniques. In this regard, the NILM technique is developed for energy disaggregation. A basic overview of the NILM from [2] is given in Fig 1.

The smart meter provides the aggregate demand from a house/sector. The NILM technique disaggregates this demand into the power of different appliances.

The problem of NILM can be solved using deep learning techniques, these techniques include Neural networks, wavelet transform, sparse coding and dictionary learning.
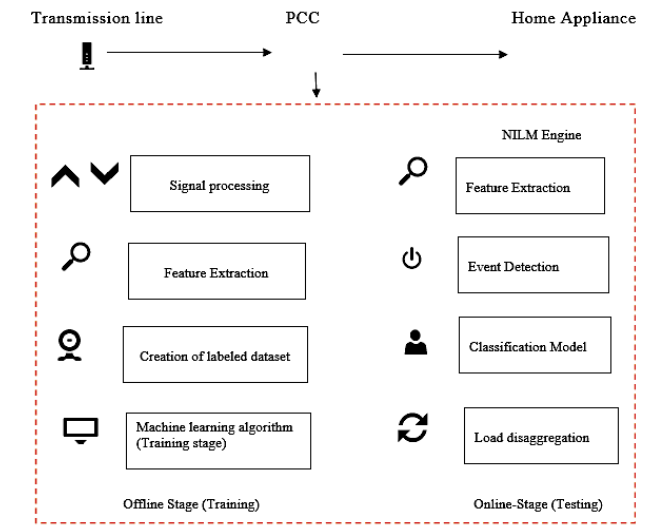
Fig. 1. Basic overview of NILM

Currently, there are several approaches to solving the NILM problem. These approaches are divided into event-based and event-free techniques. This research covers the topic of dictionary learning and proposes an improved NILM method through dictionary learning based on event detection of appliances.

The remaining paper is organized as follows: The literature review is in Section II. Section III explains the methodology of the research. Some sample outcomes of the technique are presented in Section IV.

II. LITERATURE REVIEW

In 1992, W. Hart et al. liked hidden-Markov Models, and their variants were employed. More recently, deep learning (DL) methods have also been used and show promise, particularly for addressing the complex challenges presented by the multi-state appliance consumption profiles.

In 2020, P. R. Z. Taveira et al. [7] proposed a NILM method in which a heuristic-type event detector algorithm did event detection. The Fireworks algorithm was used to optimize the events classification process. A random forecast classifier was used to classify the events. The proposed hybrid approach was tested by using a publicly available BLUED data set [10]. The results were compared with previously published techniques to validate the proposed approach, and the event classifier results were compared using data samples.

In 2016, S. Lin et al. [11] proposed a quadratic programming method for the NLIM method. Substantial laboratory and simulation tests have been demonstrated to improve event identification accuracy. For operation event detection, a cumulative sum sliding window method was used. Six different features are needed for ten different appliances, such as current harmonics, current, properties of the I–V curves, reactive and real power, and instantaneous power. The proposed approach showed 90% accuracy to the event, and the recognition and

disaggregation of energy to individual appliances showed less than a 1% error. This approach is suitable for residential and commercial buildings.

Yuanmeng Zhang et al. [12] used the convolutional neural network (CNN) feeding differential inputs. CNN used several kernels (filters) for feature detection. The number of filters used varied with complex power dynamics. This algorithm was single-tasked, i.e., it can be used for a single appliance, and a different model is required for other appliances.

In 2020, A. Siddiqui and A. Sibal [13] used an unsupervised deep learning approach for energy disaggregation. The noise problem was removed using the Denoising Autoencoders (DAE) approach to generate real data excluding noise. However, the efficiency of this approach was around 60 percent.

In 2017, N. Sadeghianpourhamami et al. [14] initially developed an approach to optimally combine attributes by considering a dataset for plug load appliance identification (PLAID) [15] initially contained 58 features. They then conducted multiple feature ranking and training sessions of the algorithm. Lastly, they picked 20 attributes, excluding all voltage and transient state power feature harmonics. The chosen features included energy of detail wavelet coefficients at the 2nd scale, total harmonic distortion (THD) of current, current root mean square, enclosed area by V-I trajectory, 3rd, 5th, 9th, and 11th current harmonic coefficients, and normalized real power, THD of non-active current.

In 2019, H. Liu, Q. Zou, and Z. Zhang [16] devised an advanced method for energy disaggregation and suggested a monitoring system that includes a composite DSWC for detecting transient events. Additionally, they used a multi-layer Hungarian matching process to match load events and converted these events into a bipartite graph optimization. A supervised clustering procedure was employed to activate the corresponding category. The input data includes RMS voltage and current, reactive and active power, and the 15th harmonic of the current.

In 2010, J. Zico Kolter et al. [17] proposed a NILM technique based on the sparse coding technique to disaggregate the power available in low resolution from a smart meter. This paper developed the discriminative disaggregation sparse coding (DDSC) algorithm for data training. This method improved the accuracy significantly. A novel technique for maximizing the disaggregation problem as a discriminative prediction problem, leading toward a simple and effective problem, was formulated. Plugwise (a European manufacturer) provided the dataset used in this paper. The data set consists of hourly data of 590 homes with different appliances in several 10-165 collected for two years. The dataset was allowed for training at a percentage of 70%, and the testing was done on the remaining 30%.

In 2018, Vaanika Singhal et al. [OBJ] proposed an NILM technique based on a multi-label classification framework. This work was based on supervised transform learning and deep-dictionary learning. This work took different power levels instead of 0/1 levels for the appliance states for better results. The testing stage is smart enough to predict the power consumption for the appliance instead of the state. This proposed technique was

validated on the REDD and PECAN data sets, which yields the best results in terms of metrics.

In 2021, Dong Hua et al. [19]proposed the NILM method that utilizes 0-1 indication for the event-based technique of NILM. This paper disaggregated the multiple appliances switched simultaneously. Mixed integer linear programming (MILP) and cumulative sum (CUMSUM) methods were used hybrid to achieve an accuracy of up to 92%. The results were validated through the REDD data set on 24-hour data. Low-frequency data and active power are used for load recognition.

In 2019 Yandong Yang et al. [20] devised a semi-supervised deep learning-based framework for multi-label appliances using a temporal convolutional network (TCN). A low sampling rate is used in this paper for self-learning and training of the load signature for single-state appliances as well as monitoring the monitor of multiple appliances. The results were validated using UK-DALE and REDD data sets. The results obtained are effective.

In 2021, Yu Liu et al. [21] proposed an NILM technique to fill the gap between what was researched and what was implemented. Deep dictionary learning was used for real-time monitoring, and high-order dynamics and sequential shift design were used to enhance the performance. The overlapping issue was solved by using sparse coding. Flexibility was added in terms of load signatures for practicability. The simulation and field measurement verified the results, and the proposed method offered good accuracy. This technique distinguished between simultaneous switching operations of electrical appliances.

In 2021, Lee et al. [23], developed a mathematical framework to enhance the accessibility and utility of electricity provision for microgrids in constrained environments. Two techniques were proposed to schedule the load limits. Improved matrices were obtained for 15 customers and improved results were obtained.

In 2021, Moradzadeh, et al. [24], presented an NILM application for feature extraction. Convolutional neural networks were provided to identify the electric devices by applying the power consumption (PC) patterns. Customer awareness was developed by providing these PC patterns. Using this method, the accuracy was higher. The presented data can be used in real-time applications.

In 2021, Azizi et al. [25] proposed a statistical method to address the NILM problem using a tiny data set. The suggested method was validated using the REDD dataset. The accuracy was higher. The reconstruction problem was also discussed in this publication.

In 2021, Liu et al. [26] suggested an approach for simultaneous actions using sparse codes. Problem formulations were based on the overlapping characteristics of the system. For real-time monitoring, a deep dictionary learning approach was utilized. The proposed technique achieved better accuracy in common load monitoring as well as overlapping issues. This study filled the gap between the theoretical and real-time studies, providing the path for new research.

In 2022, Y. Liu et.al [27] explored the potential of non-intrusive load monitoring (NILM) as a technology for enabling smart energy consumption by disaggregating energy use in a user-friendly manner. It addressed the challenge posed by individual users' customized energy use patterns, which created challenges and opportunities for implementing NILM effectively.

In 2024, A. Majumdar [28] proposed a disaggregation technique based on convolutional dictionary learning to overcome the shift-invariance limitation. The proposed technique was compared with traditional dictionary learning approaches as well as several deep learning methods like state-of-the-art using benchmark datasets. The results demonstrated that the lodged convolutional dictionary learning approach outperformed other techniques, highlighting its effectiveness in improving energy disaggregation accuracy and overcoming the shift-invariance challenge.

In 2024, Y. Liu et al. [29] presented a novel MLMoCo approach for self-supervised feature representation in non-intrusive load monitoring (NILM). MLMoCo contrasts augmented versions of the sample with instances from other samples using unlabeled aggregate load data, enabling NILM without the need for labelled data for each appliance. A momentum encoder was used to update parameters, and an event-based data augmentation method generated distinct yet related positive pairs for learning. Experimental results demonstrated significant performance gains, showcasing the potential of MLMoCo to enhance NILM's practicality and improve energy efficiency in buildings.

The NILM techniques available in the literature are broadly based on mathematical, statistical and artificial intelligence techniques. These techniques have pros and cons based on their ability to tackle the problem.

III. MATHEMATICAL MODELLING

In this paper, the disaggregation of load is based on several steps and dictionary learning follows the steps given below in the Fig 2.
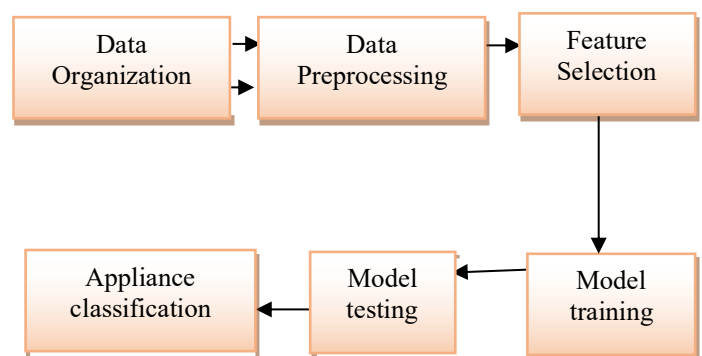

Fig. 2. Analysis flow chart

A. Data Organization and Data Pre-Processing

Disaggregation of the loads requires the training of the data. The question that arises here is which data is to be used and whether it is safe to use someone else's data. For this, the datasets available in the research are open source. These data sets have different features based on their specialty. These data sets work for features like reactive power and real, current, voltage, V-I

trajectory, power factor and harmonic distortion. The sampling rate varies from 1 Hz to 17KHz. The data sets acquire the data from different numbers of houses. These datasets can/can't perform well in real-time monitoring. It depends on the researchers which kind of feature they require from datasets. The datasets are REDD, Pecan Street, WHITED, UK-DALE and REFIT. These are tested, modelled, and trained based on data from different house appliances.

B. Feature Selection

After feature extraction, a features selection procedure is adopted to lessen the number of input features to the model. This facilitates the model for fast learning and interpretation and reduces computation costs. Weight with the regulation term is used to maximize the prediction accuracy of classification. This research uses the appliance ON/OFF value and aggregate demand.

C. Dictionary Learning

In 2010, J. Zico Kolter et al. [17] gave the basic concept of dictionary learning using a sparse coding technique, as shown in Fig 3.
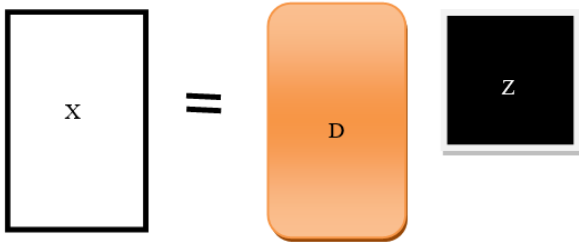

Fig. 3. Schematic of Dictionary Learning

The Load signature LS changes when the appliance is ON/OFF, which changes the aggregate demand. This LS change is detected by the dictionary learning, and the model is trained and tested for the results. This technique trains the data over time from a smart meter. The consumption is expressed as Xi for i appliances, and for every i, the data is trained, and a dictionary is learnt as Di so that the activation functions for this are expressed as Z_i. The whole process can be computed as (1).

$$Xi = Di\ Zi\ i = 1, \dots, N \qquad (1)$$

This can be solved by the following minimization (2).

$$\min_{Di,Zi} \| Xi - DiZi \|^2 + \lambda \| Zi \|^2 \qquad (2)$$

During the actual operation, simultaneous operation of the appliances occurs. The assumption is made in dictionary learning that the aggregate demand from the smart meter is the sum of individual demands; thus, if X is the total power for N appliances, then the model is given as (3).

$$X = \sum Xi = \sum Di\ Zi \qquad (3)$$

The following sparse recovery model given in (4) is used to solve the above (3):

$$\min_{Z1,\dots,ZN} \left\| X - [D1 \quad \dots \quad DN] \begin{bmatrix} Z1 \\ : \\ ZN \end{bmatrix} \right\|_1^2$$
$$+ \lambda \left\| \begin{bmatrix} Z1 \\ : \\ ZN \end{bmatrix} \right\|_1 \qquad (4)$$

As this is a convex problem, so once the loading coefficient is determined, the power consumption can easily be computed by (5).

$$\hat{X}_i = Di\ Zi\ i = 1, \dots, N \qquad (5)$$

D. Model training

To achieve the results, the data is divided into three segments. For every appliance, 70% of events are allocated for training, 10% for validation, and 20% for testing. Cross-validation is then conducted on the training set to prevent overfitting. The optimal configuration settings for the methods are derived from the cross-validation outcomes, and the final performance is assessed on the test set.

E. Model testing

The estimation of the test set performed algorithm. Dictionary learning significantly improves the performance on our energy demand. In this problem, the structured prediction maximizes the disaggregation performance.

F. Appliance classification

The accuracy of appliance classification determines the performance of the proposed algorithm. For this purpose, F1 score, recall and precision are used to judge whether appliances are classified correctly or have any classification problems.

For the F1 score, there are two objectives to be achieved as r1 (Precision) and r2 (recall), given as (6) and (7).

$$\text{Maximize } r_1 = \frac{TP}{TP + FP} \qquad (6)$$

$$r_2 = \frac{TP}{TP + FN} \qquad (7)$$

where,
    TP: True Positives,
    FN: False Negatives.
    FP: False Positives.
F1 score is given as (8).

$$F1 = \frac{2 * r1 * r2}{r1 + r2} \qquad (8)$$

Another indicator to judge the performance of the appliance classification algorithm is its processing time.

IV. RESULTS AND DISCUSSION

The ECO [30] dataset was used to evaluate the proposed algorithm's conduction. It contains 6 house data for one year. This study's installed smart energy meter samples the aggregate power every second. This means that at each one-second interval, the meter records a new data point representing the total power consumption at that moment. The dataset also gives the

3-phase current, voltage and power. It also consists of the phase angles of different phases. However, the disaggregated demand is only available in real power. The frequency of the data is also 1 Hz. The detail of the appliances used is given in Table I

TABLE I Specifications of dataset

Data set	Sampling rate	No. of Houses	Major appliances	Sparse code	Dictionary
ECO	1 sec	6 houses	Freezer, Dryer, Fridge, Coffee Machine, Washing Machine, Kettle, PC.	OMP	KSVD

A. Simulations and results

The dictionary learning algorithm needs to be capable of distinguishing the features of individual appliances to classify them and separate their consumption patterns from the overall household aggregate. The dataset includes power consumption information for various appliances, with 30% reserved for testing and 70% for training over a week's duration. The aggregate data comprises multiple measurements from house 1, where the aggregate demand fluctuates between 50 watts and 1.37 kW throughout the duration. To assess the effectiveness of the proposed algorithm, the aggregate demand of different appliances is taken in ON/OFF values as 0 and 1, respectively. The plot of aggregate demand for different appliances is given in Fig 4.
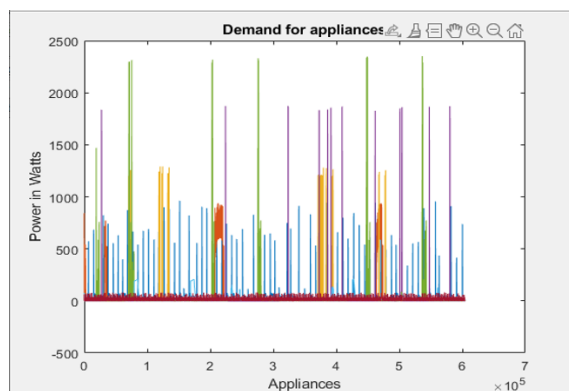

Fig. 4. Aggregate Demand

In Fig 4 it can be seen that there are seven different appliances and power is shown in terms of watts. The demand of the appliance's changes with the time. The minimum power an appliance can possess is its OFF condition which is zero. And the maximum power that an appliance possess is 2200. These appliances include fridge, dryer, Coffee machine etc.
The performance evaluation of the proposed algorithm aggregate demand of different appliances is taken in ON/OFF

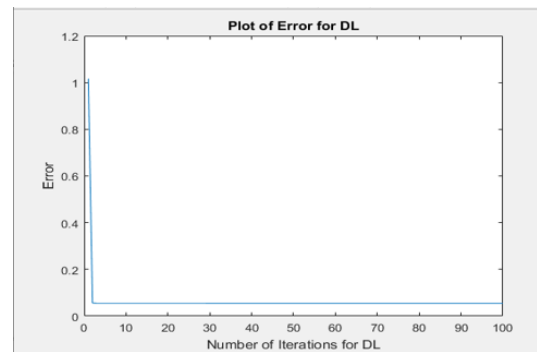value as 0 and 1, respectively. The training error of the house one is shown in Fig 5.

Fig. 5. Error of Dictionary Learning

From Fig 5, it can be seen that the model is trained on 100 iterations, and with each iteration, the error decreases. At the 1st iteration, the error is 1.01; at the 5th iteration, the error is 0.065; from the 11th iteration to the 100th iteration, the error decreases from 0.055 to 0.054.
The data is tested on the 3-day data, and results are obtained. For the performance evaluation, the recall, precision, and f1-Score are calculated for different appliances, as shown in Table II

TABLE II Performance evaluation

Appliances	Precision	Recall	F1-Score
Fridge	0.91	1.00	0.95
Dryer	1.00	0.73	0.84
Kettle	1.00	0.98	0.99
Coffee Machine	0.87	0.87	0.87
Washing Machine	0.88	0.76	0.82
PC	0.87	0.97	0.92
Freezer	0.15	0.75	0.25
Average	0.81	0.86	0.80

The results are improved with this technique. Almost every appliance is showing an F1 score greater than 0.8. These results are compared with the [27] and are given in the Fig 6.
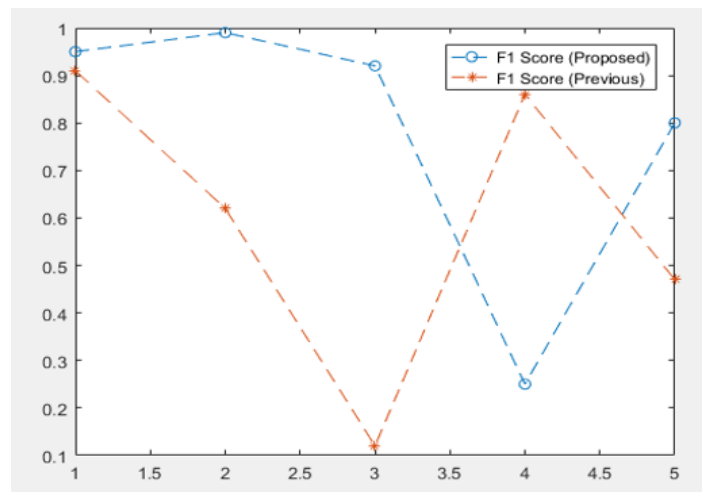

Fig. 6. Comparison of the proposed to previous

The figure above shows the F1 score of the proposed technique. The F1 score of the proposed technique for the fridge has improved from 0.91 to 0.95. For the dryer, it improved from 0.62 to 0.99, which is a very significant improvement. For the freezer, the change can be seen from 0.25 to 0.86, which shows the significance and importance of this algorithm in energy disaggregation and demand-side management. The F1 score is greater than the previous technique, and the average F1 score is also improved from 0.47 to 0.8.

V. CONCLUSION

This proposed technique presents energy disaggregation through an improved dictionary learning technique for labelled ECO datasets. Specifically, this algorithm takes the ON/OFF values of the appliances and trains them according to the given aggregate demand using OMP and KSVD algorithms. This technique has yielded significant advancements in enhancing energy efficiency and understanding consumption patterns at a granular level. Our study has demonstrated a remarkable increase in the average F1 score from 0.47 to 0.8, showcasing the effectiveness of this approach. By effectively separating aggregated energy signals into individual appliance ON/OFF events, we have provided valuable insights for energy management and conservation efforts. These results underscore the potential of the dictionary learning technique to revolutionize the field of energy disaggregation, offering a pathway towards more intelligent and sustainable energy usage in the future.

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