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Energy Disaggregation in Smart Home Appliances: A Deep Learning Approach

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Abstract—Energy management in smart homes is a hot topic due to the growing concerns on global energy depletion and environmental pollution. Non-Intrusive Load Monitoring (NILM) technique is an efficient alternative for the management of energy consumption in smart homes. NILM-based approaches analyze changes in the voltage and current going into a home and deduce what appliances are being used as well as their individual energy usage. This paper introduces a personalized appliance recommendation system based on NILM. The proposed algorithm for the recommendation system has three main stages: Denoising Autoencoder (DAE)-based NILM, term frequency-inverse document frequency (TFIDF)-based classification, and recommendation. DAE is combined with the NILM approach to clean the noisy data. The household preferences and requirements are then identified through NILM method. TFIDF classification method is utilized to quantify and analyze the energy tags by assigning them weights. The recommendations on the appliances' usage is provided to the users through the cosine similarity technique. Our proposed technique is validated on a Residential Energy Disaggregation Dataset (REDD). According to the simulation results, accuracy of this energy management approach is about 60%.

Keywords: Appliance recommendation system; Energy management; Energy disaggregation; Deep learning; Smart home.

I. INTRODUCTION

In recent years, due to the increase in energy demand and fossil fuel consumption of the world's growing population, home energy management based on household consumption behaviors is introduced. Non-Intrusive Load Monitoring (NILM) method is known as an innovative approach for optimizing household energy usage in smart buildings. Energy consumption patterns are collected and utilized in NILM algorithm to disaggregate energy in a building [1]. Recently various studies are conducted on the NILM-based energy management of buildings along with recommendation systems. The household requirements and preferences are identified through NILM methods, and the recommendations on the appliances' energy allocation is generated by the recommendation systems.

In the context of household energy management, machine learning-based approaches have received considerably more attention than Hidden Markov Model (HMM) techniques or meta-heuristic approaches. Different machine learning techniques have been applied for the management energy consumption in smart buildings over the years; For instance, the studies in [2], [3], [4] developed learning-based algorithms for energy management in the context of smart cities. Authors

in [2] proposed an approach based on machine learning for monitoring energy consumption in thermal systems of a smart house. In [3], a learning-based security infrastructure is introduced for smart building appliances. In this paper, a deep learning approach based on NILM is proposed for the management of energy consumption in smart homes. Since aggregated energy consumption data is usually noisy, a denoising autoencoder approach is integrated into the NILM algorithm to clean the data from noises. Once the data is classified using NILM method, recommended consumption patterns are generated for the appliances through the recommendation system. In addition, the appliances' specifications are compared and provided to the residents for optimal decision making. The rest of the paper is organized as follows. Section II provides an overview of the related works in the field of learning-based NILM approaches for energy disaggregation. Our proposed energy management technique is presented in section III. The simulation results are shown in the next section. Section V includes the conclusions.

II. LEARNING-BASED NILM APPROACHES

Non-intrusive load monitoring (NILM) technique was first introduced in 1980 [5]. The amount of energy consumed in a building is equal to the summation of energy consumption in each of the building appliances. Therefore, energy consumed in N appliances during time period t can be calculated as follows.

$$y(t) = \sum_{i=1}^N y_i(t) + e(t) \quad (1)$$

where N denotes the number of appliances. $y_i(t)$ is the energy share of appliance i at time t , and $y(t)$ is the total energy consumption in N appliances. $e(t)$ denotes the undesired noises. The electricity consumption data can be learned and analyzed through three main algorithms: supervised, unsupervised, and evolutionary algorithms. In a supervised learning, labeling energy data is required. Labeling data in supervised learning can be accomplished by installing more electric meters in the house and collecting appliances' attributes and their associated consumption data. Artificial neural network (ANN)-based NILM approach were first introduced for analysing the energy data (consumed in building appliances) [6]. Deep learning neural networks are known to be efficient for energy disaggregation in smart homes; however, the execution time for training a deep neural network can be very long [6], [7]. Studies in [8], [9] utilized *LSTM* deep learning approaches for

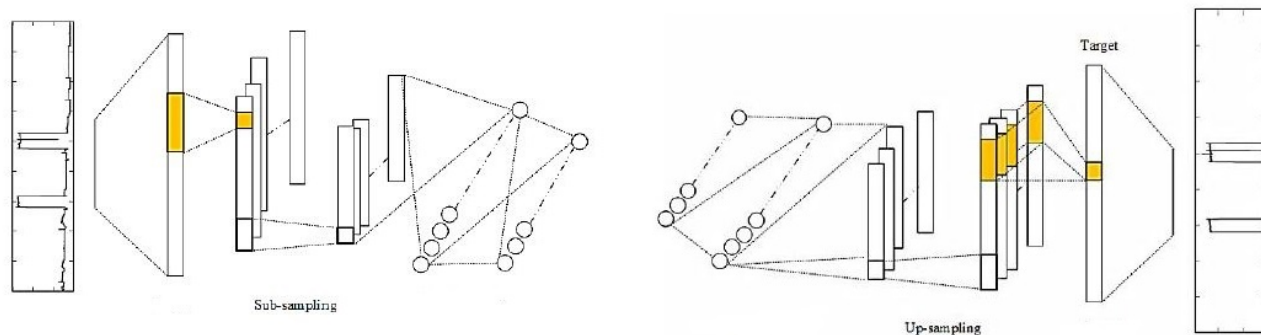


Fig. 1: DAE topology

the fault detection and diagnosis in building appliances. Restricted Boltzmann Machine (RBM) is applied as the learning algorithm for NILM. It is worth mentioning that the electricity consumption data is usually noisy, and Denoising Autoencoder (DAE) approaches can be applied to the datasets for generate pure data without noise.

Supervised NILM methods require training; however, unsupervised NILM approaches do not need training. Therefore, unsupervised NILM methods are more reliable and affordable than the supervised approaches. Also, unsupervised NILM techniques are categorized into three main groups: (1) Unsupervised approaches that do not require data labeling. These approaches are usually based on Hidden Markov Model (HMM). (2) Unsupervised approaches that require data labeling. These methods utilize the labeled data to disaggregate energy consumption in buildings. deep learning-based NILM approaches are categorized in this group of unsupervised techniques. (3) Unsupervised approaches that do not require data labeling or even training. These approaches can analyze the energy consumption data without having any measured labeled data.

Hidden Markov Model (HMM) is a statistical modeling approach in which the system being modeled is assumed to be a Markov process. HMM models the evolution of observable events that are not directly observable. These events are dependable on factors. The observed events in this process are known as symbols, and the factors underlying the observation are known as states. HMM approach is very effective for unsupervised learning of household energy data. The prominent drawbacks of HMM are [10]: (1) There are so many unstructured parameters in HMMs. (2) HMMs are not capable of detecting dependencies between hidden states. (3) In a constrained HMM, a small fraction of a distribution in a space can be considered. (4) To avoid complication of the model, it is required to initially set the number of hidden states. (5) The data is distributed geometrically, however, real data is not distributed like that.

Genetic Algorithm (GA) is a search heuristic (metaheuristic) process that is also being used for NILM applications. GA is utilized to detect and analyze the appliances' entities and energy profiles [11]. GA algorithms are useful for observing

and detecting states with repetitive profiles. In some studies, GA approach is used along with ANNs for demand side management applications. Differential evolution (DE) is a population-based metaheuristic algorithm that uses GA operators, such as creation, selection, crossover, mutation. DE is another evolutionary algorithm that is being utilized for NILM [12].

NILM methods are also useful for identifying household appliances that use the most electricity in homes. The recommendations on energy consumption are provided in this way to the end-users. The recommendations generated through NILM approaches are not very reliable because NILM approaches use HMM methods for identifying the residents' requirements and preferences, and HMM is a statistical approach which may result in incorrect identifications.

III. PROPOSED METHODOLOGY

Recommender systems are powerful infrastructures for improving energy efficiency in smart homes. They can provide useful information on household energy consumption, and assist the residents in energy-efficient decision-making. The objective of this study is to extract preferences of building residents by learning and analyzing energy consumption profiles. In addition, we are aiming to develop a method that can balance between comfort and energy efficiency for the users, and can provide useful information on the energy consumption and characteristics of building appliances. Our proposed infrastructure consists of 8 stages: pre-processing, Denoising Autoencoder (DAE), load identification, identifying users' preferences and requirements, generating profiles for the energy consumed by the end-users, generating profiles for the energy consumed by the appliances, TFIDF, and generating personalized recommendations. Each of these stages are explained as follows.

- Pre-processing: Pre-processing stage consists of three steps; normalization, selection of items, and selection of samples. By normalization, all the quantities are normalized between 0 and 1. Next, appliances are chosen, including microwave, stove, cooler, heater, refrigerator washer, dish washer. Four days of data is sampled for testing, and the rest of the data is used for training.

- Denoising Autoencoder (DAE): DAE approach is utilized to remove noises from the datasets. Denoising process is as follows.

$$y(t) = y_j(t) + v_j(t)$$

$$v_j(t) = \sum_{i=1, i \neq j}^N y_i(t) + e(t) \quad (2)$$

where v_j above denotes the data noise that need to be removed. Fig. 1 shows the topology of Denoising Autoencoder.

- Load identification: The household loads are identified in this stage to extract the users' preferences in the next step of algorithm.
- Users' requirements identifications: In this step, users' preferences and requirements are extracted based on the frequencies of appliances usage. NILM method is utilized in this stage. For instance, if the heater was frequently being used, it will be considered as the user's requirement (meaning that user needs to frequently use this device).
- Users' energy consumption profiles: Energy consumption of the users (their trends) are collected.
- Appliances' energy consumption profiles: Energy consumption of the appliances are collected and then will be used for training and learning purposes.
- TFIDF: TFIDF is used to assign weights to the energy tags. This method is used to classify and label the datasets (if needed).
- Personalized recommendations: After learning the available profiles and analyzing them, personalized recommendations on energy consumption are provided to the end-users.

IV. SIMULATION RESULTS

The simulations are performed in Python. The optimization algorithm was ADAM, and the mean squared error (MSE) is used to validate the performance of learning algorithm. NILM is applied to REDD datasets [13]. REDD provides energy consumption datasets of 6 buildings during 117 days (with 268 embedded sensors).

Fig. 2 shows the relative error, F1 score, accuracy, precision, and recall values of NILM. According to these plots, accuracy of the deep learning-based NILM approach is 80%, which shows a significant improvement in learning (compared to the HMM). Fig. 3 shows performance of TFIDF classification algorithm. According to this pattern, 185 tags out of 230 are labeled as appliances. The accuracy of TFIDF is 85%, which is satisfactory.

Fig. 4 shows the recommendation on energy consumption for 6 households, and Fig. 5 compares the results of energy savings using the proposed approach and a baseline approach.

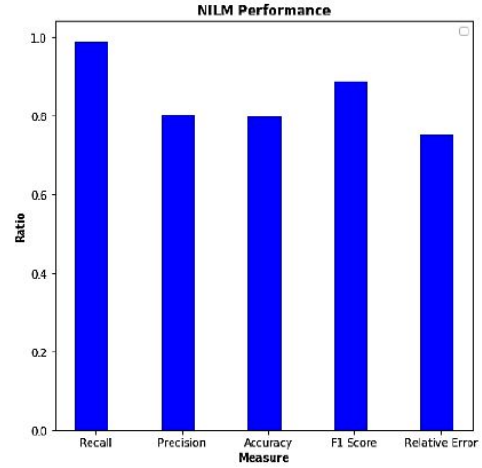


Fig. 2: NILM performance

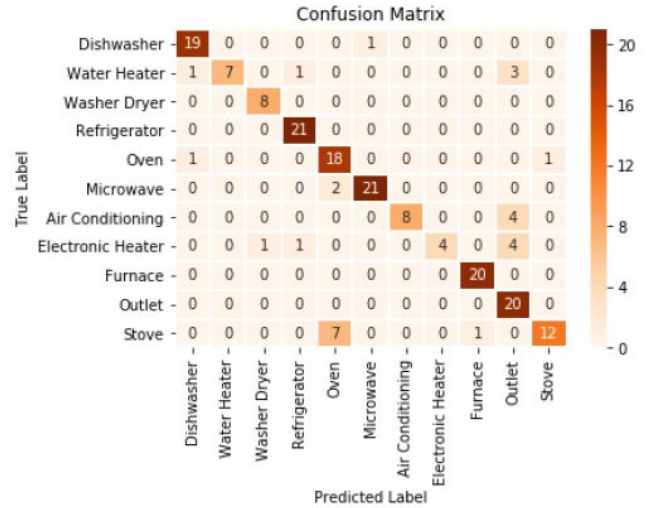


Fig. 3: TFIDF performance

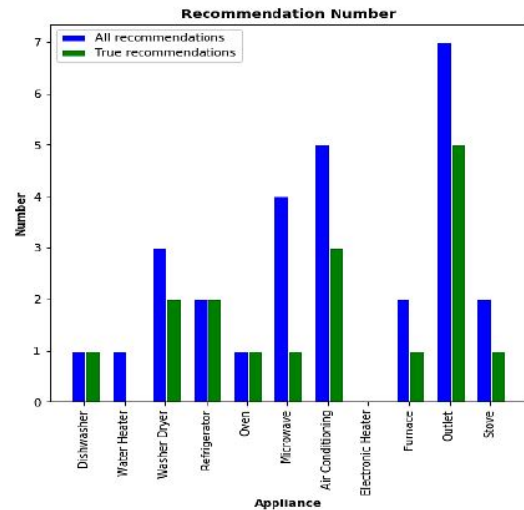


Fig. 4: Recommendations on energy consumption

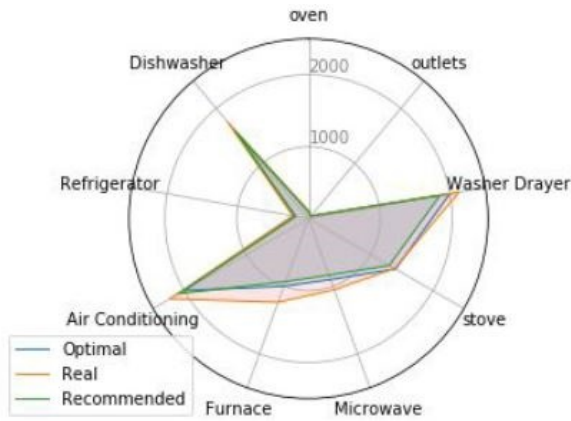


Fig. 5: Comparison of the energy usage using the proposed approach and baselines

V. CONCLUSION

In this paper, an energy management approach based on NILM, TFIDF, and DAE techniques is developed. Simulation results proved the efficiency of our proposed strategy. Accuracy of the developed NILM algorithm is 85%, and TFIDF method showed 80% accuracy. For future research, a repetitive learning mechanism can be tested and included in the proposed strategy.

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