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Assessing the Effectiveness of Supervised and Semi-supervised NILM Approaches in an Industrial Context

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Non-Intrusive Load Monitoring (NILM) is a technique that aims to estimate the energy consumption and operational status of individual appliances in a building by analyzing only the aggregate power usage data. This technique plays a crucial role in demand-side management and energy conservation efforts by providing detailed information about the energy consumption patterns of individual appliances. Naturally, NILM is considered as a supervised problem, that is a Regression and Classification problem. Various Deep Neural Network models have recently been developed for NILM regression and classification tasks. However, training deep neural networks requires a significant amount of labeled data and collecting consumption data over a prolonged period exposes consumers to severe privacy risks. Hence semi-Supervised learning is also used for NILM. Furthermore, most NILM research uses datasets from the residential sector, and only a handful of research uses datasets from tertiary sectors. This paper comprehensively studies the performance of supervised and semi-supervised NILM algorithms based on a tertiary sector dataset named the GreEn-ER dataset. The semi-supervised deep learning NILM method performs classification tasks, whereas the supervised method performs classification and regression NILM tasks simultaneously. Based on the analysis, it is concluded that the presented NILM algorithms can yield satisfactory results using the tertiary sector's consumption dataset. Additionally, the ideal input parameters that facilitates the performance of the both NILM algorithms are also noted.

CCS CONCEPTS • Computing methodologies • Machine learning algorithms

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Additional Keywords and Phrases: NILM, Energy Disaggregation, Supervised learning, Semi-supervised learning, Deep Learning.

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1 Introduction

In the past decade, there has been a rise in the need for electricity as it is the primary energy source used in industry, agriculture, and daily life for people around the world. The increased electricity consumption leads to the burning of large amounts of fossil fuels, negatively impacting the environment and climate [1]. Therefore, reducing electrical energy consumption not only helps the environment but also benefits the economy and society [2]. One of the ways to increase energy saving is by monitoring users' energy consumption in residential or commercial environments. According to a study, 4.5% of energy can be saved when residential users are provided with their consumption feedback [3]. The percentage increases even more when users are provided with the information of the consumption made by their individual electrical appliances [4]. Appliance load monitoring system (ALM) can provide the detailed information about of energy consumption made by individual appliances using smart meters [5]. ALM helps to develop robust energy management systems and can identify faulty appliances and appliances with high energy consumption.

There are two categories of ALM systems – Intrusive Load Monitoring (ILM) and Non-intrusive Load Monitoring (NILM). Figure 1 represents the block diagram of both ILM and NILM. Typically, ILM involves placing sensors at the end of users' appliances to monitor their consumption. Although ILM provides highly accurate information on appliance energy consumption and operational states, installing and maintaining smart meters attached at the end of each appliance will increase the economic cost for users and expose them to the risk of privacy leakage [6]. Thus, NILM is considered as the alternative solution, where appliance-level energy consumption and states are determined from the aggregate power load obtained from the main meter of users' residential or commercial units.

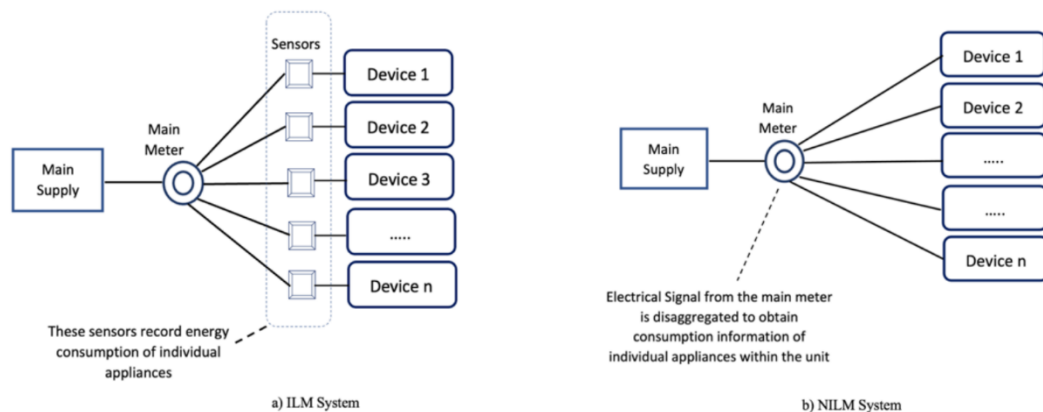


Figure 1: Block Diagram of two categories of ALM systems

Non-intrusive Load Monitoring, often termed as Energy Disaggregation, is the process of breaking down the aggregated load obtained from main meter into the energy consumed by the individual appliances [7]. This technique was first proposed by Hart in 1992 [9]. By accurately identifying and monitoring individual appliances' energy consumption, NILM can provide valuable insights into energy usage patterns and facilitate informed decision-making for optimizing energy efficiency. A typical NILM framework is seen in Figure 2, which consists of the following steps [11,12]:

- First step is data acquisition. This step involves the collection of electrical measurements from a single point or multiple points in a building, typically using smart meters or submetering devices.
- Pre-processing is then performed to clean and normalize the acquired data, removing noise, handling missing values, and aligning timestamps.
- The next step is feature extraction, where relevant features are derived from the pre-processed data. These features may include statistical measures, frequency domain analysis, or time-frequency analysis, capturing the characteristics and patterns of different appliances.
- In the appliance identification step, machine and/or deep learning algorithms are employed to classify the extracted features and associate them with specific appliances. This step involves training a model using some labelled data, allowing the model to learn the distinct energy consumption patterns of different appliances.
- Finally, energy disaggregation is performed, where the total energy consumption is disaggregated into individual appliance-level consumption based on the identified appliances' energy signatures. This step typically involves mapping the identified appliances' energy consumption profiles to the aggregated data, allowing for estimation of the individual appliances' contributions to the total energy consumption.



Figure 2: Steps of a NILM framework

NILM is often framed as a supervised learning problem comprised of regression and classification tasks. The regression based NILM approaches estimate the energy consumption of individual appliances, while in the classification approach, the aim is to identify the operating states (usually On/Off states) of appliances from the aggregated power. Most NILM research focus either on classification or regression NILM problems and not both at the same time. It is important to note that supervised NILM approaches heavily rely on labeled training data, where the power consumed by each appliance are recorded with the total power signal. Often the process of labeling training data is time consuming, compromise the privacy and requires manual intervention which is unfeasible for practical deployments [11]. The Semi-supervised NILM approaches address the limitations of the supervised approach by leveraging small amount of labeled and large amount of unlabeled data. Incorporating unlabeled data exposes the semi-supervised NILM models to vast amount of available energy consumption data, which scales up NILM systems. Moreover, utilization of unlabeled data can also contribute to developing models that can handle new appliances and adapt to changing energy usage patterns [13,14].

Historically, NILM research has relied on residential datasets due to their availability and easier access. The consumption data are collected from various residential units equipped with smart meters, recording the electrical measurements necessary for appliance-level energy disaggregation. Majority of NILM research uses residential datasets and focusing solely on such datasets limits the generalization and applicability of NILM techniques in other sectors. The tertiary sector comprises of commercial, industrial, and institutional buildings which have distinct energy consumption characteristics compared to residential buildings [15]. Using tertiary sector datasets in NILM research facilitates the development of NILM models that can handle the unique challenges posed by commercial buildings, industrial facilities, and public institutions.

In this paper the above problems are addressed by evaluating the performance of the two NILM models, one supervised and the other one semi-supervised, using a novel dataset from tertiary sector called the GreEn-ER dataset [10]. Both NILM models are developed using deep learning-based architectures. The supervised NILM model performs both classification and regression tasks simultaneously. The semi-supervised learning model is based on Mean-Teacher learning model. In a nutshell, the main contributions of the paper are as follows: (i) Presenting one supervised and one semi-supervised deep learning based NILM models. (ii) Introducing the GreEn-ER NILM dataset. (iii) Performance of the two NILM models using the novel dataset.

The rest of the paper is organized as follows. Section 2 discusses the GreEn-ER dataset and how the data is prepared to train and evaluate both models. Section 3 elaborates the frameworks of supervised and the semi-supervised NILM models used in this study, along with a brief description of the evaluation metrics. Section 4 elaborates the model implementation, experimental results and discussion. Section 5 summarizes the contributions and ideas for future work.

2 GreEn-ER Dataset

The dataset utilized in this paper is called the GreEn-ER dataset [10] which is a novel dataset gathered from the Grenoble INP Ense3 and G2E Lab at the Institut Polytechnique de Grenoble in Grenoble, France. From January 2017 to December 2021, this dataset captures the individual usage of six distinct appliances as well as the overall aggregated power signal.

2.1 Dataset Description

The dataset is comprised of the aggregated power signal and individual energy usage of six different appliances, namely Ventilation, Socket plugs, Lighting, Other electricity, Cooling and Heating. Each reading is recorded at an interval of one hour, for which GreEn-ER dataset is considered as a low frequency NILM dataset. Following is some of the advantages of low frequency NILM datasets [16,17,18]:

- The reduced frequency dataset reduces the data acquisition and processing requirements, making it easier to collect and handle large-scale datasets. The researchers can also analyze longer periods of energy consumption with fewer computational resources.
- By sampling at lower frequencies, these datasets provide a broader perspective on appliance usage over extended periods, enabling researchers to analyze daily, weekly, or monthly consumption trends. Long-term patterns are valuable in understanding appliance behaviour, detecting changes in energy consumption patterns, and developing more accurate load disaggregation models.

Low-frequency NILM datasets often exhibit a higher signal-to-noise ratio compared to high-frequency datasets. The lower sampling rate eliminates high-frequency noise, resulting in cleaner power signal data. This enhanced signal quality improves the accuracy of feature extraction and load disaggregation algorithms, leading to more reliable and precise NILM outcomes.

Figure 3 represents the pie chart of the usage of six appliances of the GreEn-ER dataset from 2017 to 2021. Most power is consumed by the Other electricity appliances which is 33%, followed by Heating which is 26%. The Cooling and the Ventilation appliances consumed 17 and 12% power respectively. And finally, the Socket plugs consumed 7% and Lighting appliance consumed 5% of the total energy recorded between 5 years' time period. Table 1 presents the maximum, mean and minimum value of total aggregated signal and consumption made by individual appliances for the entire dataset and individual years.

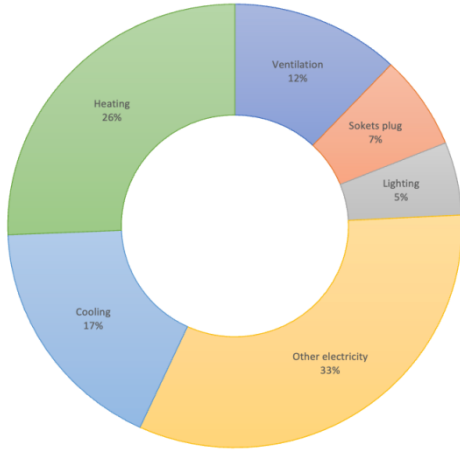


Figure 3: GreEn-ER consumption by end use from 2017 to 2021

2.2 Dataset Preprocessing

The NILM datasets contain aggregate power load as well as individual appliance usage and do not include an explicit label for the operational states of the appliances. Classification NILM tasks predict the appliance states based on the aggregate signal, and it is difficult to detect whether a specific appliance is switched On or Off based just on its power consumption. The GreEn-ER dataset only contains consumption information and for NILM classification task of the supervised approach, it is important to obtain the states of the individual appliances for each recorded measurement. In order to obtain states of the appliances of the dataset at an instance, a thresholding technique titled Middle Point thresholding is adapted in this paper [19]. Table 2 shows the threshold values obtained for the individual appliances after applying Middle Point thresholding. If the consumption value of an individual appliance is more than or equal to the thresholding value of the respective appliance, then the appliance is assigned value 1 (On state). Otherwise, the appliance is assigned value 0 (Off state). For the semi-supervised learning approach, similar dataset is copied but now, random instances are selected where appliances' states are assigned value -1 which means unlabeled. Additionally, the consumption value of the appliances is removed from the dataset used for training and evaluating the semi-supervised learning approach. In other words, supervised learning of this paper used one set of GreEn-ER dataset and semi-supervised learning used another separate set of datasets. For each learning approaches, 70% of the dataset is used for training and 30% is used for testing.

3 Description of learning approaches and Evaluation Metrics

One supervised learning approach and one semi-supervised learning approach is used to evaluate the GreEn-ER dataset. Both of these approaches used deep learning architecture for disaggregation task. Supervised learning approach performs both classification and regression task simultaneously, meanwhile the semi-supervised approach leverage the small amount of label data and large amount of unlabeled data to classify states of all six appliances [20]. In this section, the description of both supervised and semi-supervised models are presented and the metrics which helps to evaluate the performance of the models are also elaborated briefly.

3.1 Supervised learning model

For the supervised learning approach, a deep learning framework based Temporal Convolution Neural (TCN) architecture is adopted. TCN is an improved version of one-dimensional convolutional neural network. The advantage of TCN lies in the integration of causal convolution, dilated convolution, and skip connection into the network structure. Causal convolution ensures that the output of time step will not use future information and will only be obtained based on convolution operations Dilated convolution allows the input of convolution to have interval sampling, and the sampling interval is determined by the dilation rate. Therefore, this allows TCN to use fewer layers and obtain a large receptive field.

Table 1: Maximum, Mean and Minimum consumption values in kWh of all appliances and aggregate power load for the entire dataset and individual years

	Total	Ventilation	Sockets plug	Lighting	Other electricity	Cooling	Heating	
Maximum Value	2037	793	980	132	971	1641	1120	Entire Dataset
Mean Value	269.09	32.43	18.40	14.30	87.8	47.08	68.99	
Minimum Value	3.13	0	0	0	0	0	0	
Maximum Value	1427	479	49.80	80	765	622	763	2017
Mean Value	298.14	36.52	18.84	16.68	89.13	53.82	83.14	
Minimum Value	25.35	0	4.22	0	0	5.84	0.25	
Maximum Value	1913.4	608	103	132	879	1641	1120	2018
Mean Value	246.46	26.58	17.99	15.59	58.38	60.70	67.19	
Minimum Value	20.49	0	3.91	0	0	0.18	0	
Maximum Value	2037	793	547	71.50	971	1599	850	2019
Mean Value	294.41	30.77	18.23	15.45	116.20	53.77	59.97	
Minimum Value	17.92	0	0.56	0	0	0	0	
Maximum Value	1167.40	322	622	65.90	537	543	724	2020
Mean Value	240.30	29.02	16.70	10.47	97.99	33.56	52.54	
Minimum Value	34.09	0.87	0	0.62	0	0	0	
Maximum Value	1180.70	569	980	68.10	215	558	691	2021
Mean Value	266.48	39.44	20.33	13.44	77.51	33.88	81.85	
Minimum Value	3.13	0	0	0	0	0	0	

Table 2: Threshold values of the appliances in kWh obtained using Middle Point thresholding

Appliances	Ventilation	Socket plug	Lighting	Other electricity	Cooling	Heating
Threshold Value	107.6	245.4	26.3	278.5	301.7	84.6

Skip connection is directly connecting the feature map of the lower layer to the upper layer and 1×1 convolution ensures the addition of the same shape of feature maps. Skip connection helps to avoid the

disappearance of the gradient when there is an increase in the number of network layers to strengthen the stability of the network. Using batch normalization and spatial dropout to each layer helps to regularize the network. [Figure 4](#) (a) shows two such layers with skip connection of 1x1 convolution that are encapsulated into a residual module. The deep TCN network is formed by stacking multiple number of these residual modules. Components of each residual block is shown in [Figure 4](#) (b). The fully connected layer on top of the seven TCN residual blocks generate all six appliances' states and power consumed when the aggregate power signal is provided to the model.

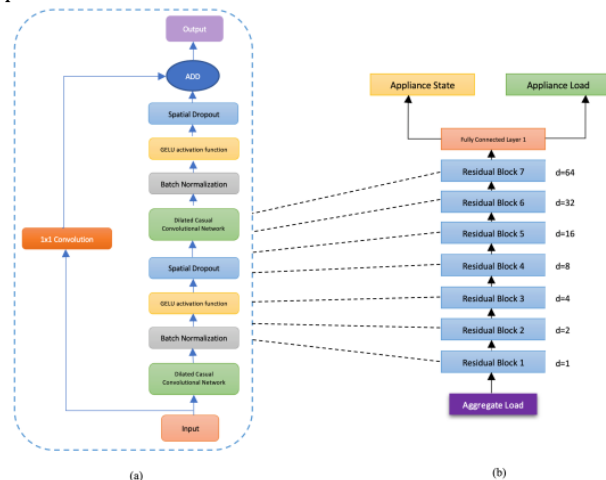


Figure 4: (a) Residual Block of the proposed TCN NILM model. (b) The architecture of the proposed TCN NILM model.

3.2 Semi-supervised learning model

The semi-supervised model is developed using deep learning architecture based on Mean-teacher model. The Mean Teacher model is a semi-supervised learning technique that has gained popularity in the context NILM. It is an extension of the standard supervised learning approach, which leverages both labeled and unlabeled data to improve the performance and generalization of the NILM model. The Mean Teacher model introduces a teacher-student paradigm, where the teacher model's weights are an exponential moving average of the student model's weights. During training, the student model is updated using labeled and unlabeled data, while the teacher model's weights provide soft targets for guiding the student's learning process. By employing the Mean Teacher model, the NILM system can effectively harness the information present in unlabeled data, leading to improved energy disaggregation performance and enhanced robustness against variations in energy consumption patterns [8]. [Figure 5](#) represents the block diagram of a Mean-teacher model. The final output for the semi-supervised model is obtained from the student network. The student and teacher network are comprised of TCN and LSTM architecture. The TCN architecture used in this model is similar to the one used in the supervised model.

From [Figure 5](#), it is observed that each network is comprised of TCN and LSTM architecture. The Long Short-Term Memory (LSTM) architecture is a type of recurrent neural network (RNN) that has been widely used in Non-Intrusive Load Monitoring (NILM) research. LSTM is designed to address the vanishing gradient problem commonly encountered in traditional RNNs, making it well-suited for sequence-to-sequence tasks, such as energy disaggregation. The key feature of LSTM is its ability to learn and retain information over long time intervals, which is crucial for capturing complex temporal dependencies in energy consumption data. The architecture incorporates a system of gates, including input, forget, and output gates, which regulate the flow of information

through the network. This gating mechanism enables LSTM to selectively update and retain information, making it effective in modelling the energy consumption patterns of various appliances in NILM tasks.

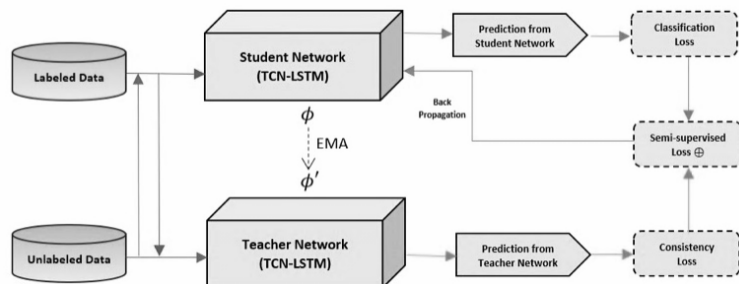


Figure 5: Architecture of the proposed semi-supervised TCN-LSTM technique for appliance states classification in NILM.

4 Experimental Evaluation

In this section, implementation details of the two models are presented and discussion is made on performance of both models using GreEn-ER dataset based on Mean absolute error (MAE), F1 score and Hamming Loss evaluation metrics.

4.1 Implementation Details

For the supervised NILM model, the filter size of the TCN is set to 3 and dilation factor for each residual block is set to 2^i where i is the residual block number. The TCN network is comprised of seven TCN residual blocks with each block having 128 filters for hidden layers. The final layer is a fully connected layer from which the final appliance states and power consumption are obtained. The spatial dropout rate is set to 0.2. The experiment was performed in Mac Mini M1 device having a Ram capacity of 8 GB and a storage of 512 GB. The device is composed of 8 core CPU and 8 core GPU.

Considering the semi-supervised NILM model, similar TCN architecture is adopted with similar number of filter size and dilation factor but here, each block has 256 filters instead of 128 filters for hidden layers. Besides TCN, the Mean-teacher model also contains LSTM architecture. The first LSTM layer consists of 64 filters with kernel size of $1*5$ and the second LSTM layer is comprised of 120 filters with similar kernel size as the first LSTM layer. A fully connected layer is attached at the end of the final layer of both teacher and student networks. The smoothing hyperparameter of the EMA is set to 0.99. The semi-supervised loss is then calculated using the classification and consistency losses and is used to update the student network with Adam optimizer. The value of the learning rate with Adam optimizer is set to 0.001. The teacher network is then updated using EMA. A total of 150 epochs was used during training.

4.2 Experimental results and Discussion

[Table 3](#) shows the MAE and F1-score of the supervised model when trained and evaluated using GreEn-ER dataset. The model had an overall MAE score of 0.37, with the best MAE score obtained by the Socket plug, having a score of 0.25, followed by cooling appliance having a score of 0.29. Heating and Ventilation appliance have a MAE score of 0.31 and 0.33 respectively. Lastly other electricity appliance obtained an MAE score of 0.42 and score of lighting appliance is 0.56. Based on the MAE score it can be said that the error in energy estimation by the supervised model for the socket plug, cooling, heating and ventilation is less than other electricity and lighting appliance. F1 scores of the [Table 3](#) represents the performance of the supervised learning model in respect to its classification task. According to the F1 scores, the model is able to predict the state of the lighting, other electricity

and ventilation appliance than the socket plug, cooling and heating appliance. The overall F1-score of the model is 0.81, showing the model’s satisfactory capability in estimating operational states.

Table 2: MAE and F1-score for the supervised NILM model

Appliances	Ventilation	Socket plug	Lighting	Other electricity	Cooling	Heating	Overall Model
MAE	0.33	0.25	0.56	0.42	0.29	0.31	0.37
F1 Score	0.76	0.52	0.94	0.83	0.49	0.68	0.81

From Table 3, Hamming Loss and F1 score for the semi-supervised model is observed. The semi-supervised model performs NILM classification tasks and so evaluation metrics traditionally used for classification problems is used here for the model’s performance assessment. Based on the HL score heating, lighting, other electricity and ventilation appliances’ states are properly predicted in contrast to socket plug and cooling. The overall HL score of the model came out to be as 0.224. For the F1-score, similar patterns are also observed where again lighting, heating, other electricity and ventilation obtained better score than the remaining socket plug and cooling appliance. F1-score of the overall model is 0.75.

Table 3: Hamming Loss (HL) and F1-score for the semi-supervised NILM model

Appliances	Ventilation	Socket plug	Lighting	Other electricity	Cooling	Heating	Overall Model
HL	0.215	0.572	0.119	0.176	0.638	0.127	0.224
F1 Score	0.65	0.48	0.79	0.73	0.39	0.71	0.75

For the supervised model, considering all data of the tertiary sector to be labelled, the overall error in estimating appliance power lies between 20 to 50%. For classifying operational states, four appliances achieved good F1 scores, meaning that most of their states were predicted correctly compared to two remaining appliances which has lower F1 scores. For the semi-supervised model, which utilized small amount of labelled data and large amount of unlabelled data, in terms of both HL and F1 score, similar appliances generated satisfactory scores meaning that states of appliances with good HL and F1 scores are predicted more accurately. In both cases socket plug appliances had lower chance of estimating proper operational states and power consumption. This might be due to the fact that various appliance having different consumption patterns might be connected to the socket plugs for which the scores for both models came out poor. It is also important to note that disaggregation task achieved by the semi-supervised model incorporated more appliance having average results whereas disaggregation task performed by the supervised model incorporated less appliance but with more accurate disaggregation results.

5 Conclusion

In this paper, detailed analysis of the performance of supervised and semi-supervised NILM models on a novel tertiary dataset is presented. First description of the novel tertiary NILM dataset along with its importance in NILM research is discussed. Next two deep learning based supervised and semi-supervised NILM models are implemented and based on standard evaluation metrics, the performance of the models on the novel dataset is accessed. It is observed that semi-supervised NILM model generated average classification results for large number of appliances, but the supervised NILM model generated more accurate results but for less number of appliances than the semi-supervised model. Future work may explore the impacts of various supervised and semi-supervised NILM model having a foundation of different deep learning architectures on datasets of other

tertiary sectors. Experimenting the impacts of tertiary datasets on NILM models enhances the scalability and effectiveness of NILM techniques in real-world scenarios beyond residential settings. In conclusion, while residential datasets have been extensively used in NILM research, incorporating datasets from the tertiary sector is crucial for a comprehensive understanding of energy consumption and the development of robust NILM techniques. The inclusion of datasets from commercial, industrial, and institutional buildings enhances the scalability, generalization, and real-world applicability of NILM techniques beyond.

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