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Analysis of Artificial Intelligence based Methods For Sensorless Disaggregation of the Residential Electric Power Signals

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Abstract

Seeking sustainable solutions for ever-increasing energy demand is one of the key priorities today. Energy conservative behavior of domestic users can enable with appliance-wise consumption statistics. Non-Intrusive load monitoring (NILM) is a popular technic to calculate appliance-wise energy consumption without using individual sensors. The availability of energy data and the use of smart meters increase the popularity of NILM in many application areas in recent years. This study presents a comprehensive analysis of the application of two key deep Artificial Intelligence (AI) families, Convolutional Neural Network (CNN) and Recurrent Neural Network (RNN) for NILM. An unbiased comparison performs in a common platform between CNN and Gated Recurrent Unit (GRU) a member of RNN family in a different dimension of NILM. Regression-based sequence to point input to output mapping was considered for comparison along with the soft association method. Both NN models were modified and improved prior to compassion. Thereafter, a rigorous comparison was performed in disaggregation performances, time taken by each NN, and computational complexity. Performance indices including, accuracy, precision, recall, and F-measure has been used for the comparison. Results provided important facts related to each NN and the relationship between architectures, appliances, activation signatures, and available volume of training data with respect to disaggregation performances.

Index Terms – Comparative-Analysis, Disaggregation, Neural Network, NILM

Introduction

Conservation of energy has become a top priority of the world today. Rapid industrialization and growth in population has led to changes in lifestyles and increased energy demand of the world. The global energy demand increased by 4.6% in 2021 as per IEA [1]. Furthermore, the world electricity demand increased by 4.5% in 2021, by over 1000 TWh. More than 60% of the world energy demand is caused by residential and commercial sectors [2]. Hence, investigating domestic level conservation mechanisms are becoming an important area of research that would benefit both the consumer and the utility. Moreover, new appliances are added every day and consumers tend to use more and more appliances for a comfortable life. Due to extended use and lower-quality appliances, the energy consumption has increased substantially over ordinary appliance consumption [3].

Monitoring of appliance use in households will help consumers to make decisions to save energy. To monitor appliances, it is required to collect appliance level electricity use data of consumers. The traditional approach for appliance wise data collection is Intrusive Load Monitoring (ILM). It requires connecting individual sensors for each appliance and connecting these sensors to a central data collection hub. It is a very challenging and an expensive task. Therefore, there has been interest in developing Non-Intrusive Load Monitoring (NILM) techniques for estimating residential appliance level electricity consumption data. The NILM approaches use household electric meter reading in real-time to estimate the electric power consumption in individual appliances without using retrofitted sensors. Once the reading is obtained from the electric meter it requires disaggregation techniques to obtain the power consumption of individual appliances at a given time. Artificial intelligence could provide an efficient and yet a powerful technique for the disaggregation of the energy signal. Hence, it is worth investigating more powerful NILM based algorithms for energy disaggregation.

Hart G.W. [4] took the first initiative for NILM in 1992 using current harmonics to disaggregate energy consumption into appliance level. Later more powerful and advanced techniques have been introduced for energy disaggregation [5]. Past studies have used different approaches that include, Graphical Signal Processing (GSP) [6], Hidden Markov Models (HMM) [7], V-I trajectory signatures, active-reactive power plots [8], and AI based algorithms [9]. Each of these techniques have demonstrated their inherited capabilities and limitations.

Most of the studies have used different types of features embedded in the aggregate energy signal to classify and disaggregate appliance level energy signals. These include steady-state features, transient features, and hybrid features. The commonly used Steady-state features are active power, reactive power, apparent power [9], current waveform, and current harmonics [11]. The features that contain information related to a state change in energy signals like transient power, current, and voltage transient [12-15] are used under the transient feature category. Some of the approaches have combined both steady-state and transient features to deliver more accurate disaggregation results [16-18]. One of the key limitations of these traditional disaggregation approaches is the need to extract these feature vectors manually.

Commonly used handcrafted feature extractors include Fourier analysis, wavelet transformation, spectral-domain representation, and others. However, these methods are highly time-consuming, complicated and subjected to a high probability of error. It is also very difficult to select the most optimal feature vector for carrying out disaggregation of the target appliance for energy consumption.

Deep Learning (DL), a subcategory of AI has been able to overcome the difficulties associated with handcrafted feature extraction. In the DL based method it automatically extracts the most optimal feature vector through self-leaning [8]. Different types of DL tools (i.e., Deep Neural Networks – DNNs) have been used in the NILM domain. These tools include Convolutional Neural Networks (CNN), Recurrent Neural Networks (RNN) with its variant Long Short-Term Memory (LSTM), Gated Recurrent Unit (GRU) and Autoencoders (AE). DNN based NILM approaches are two-folded. One such approach is to identify the availability of the target appliance within the aggregate signal and the other is to predict the target appliance's power consumption by analysing the aggregate signal. In addition to that, DNNs are used to identify the appliance and it is called appliance classification. DNNs are very good at extracting appliance specific nuclear features that are hidden in appliance activation signatures, V-I trajectories, power plots, and transient shapes.

CNN is the most commonly used NN type that is associated with the NILM domain. CNNs have been mainly used for computer vision related applications such as image recognition, and object identification due to its capability of distinguishing complex patterns. Hence, CNNs could be used to filter out appliance specific short sequence power variation from the aggregate signal. However, CNNs accept a snapshot of a very short aggregate signal window compared to the entire signal length. Hence, CNN only considers temporal information captured within the short window. The appliance energy consumption signal is a Time Series Signal (TSS) that has a strong relationship with the power consumption of nearby timeslots. Pre-programmed modern appliances such as washing machines, microwaves, and multi-cookers explicitly present the temporal relationships. Hence, capturing the temporal relationship of power consumption between consecutive time slots will enhance the accuracy of energy disaggregation.

RNN and its variants such as RCNN, LSTM, and GRU are capable of retaining memory of previous input and output within the NN. Hence, these NNs can be used to capture temporal information within the energy signal to enhance the accuracy of the disaggregation process. However, RNNs and its variants consume a substantial amount of computer processing power and memory compared to other NNs such as CNN. Energy disaggregation can be implemented in a decentralized geographical layout such as within individual household smart meters that have very low processing power and memory. Hence, it is essential to balance the trade-off between accuracy and resource requirement when implementing commercial NILM solutions.

This paper presents how DNN can be used to disaggregate a composite energy signal into appliance wise individual energy consumption leading to conservation of energy. Moreover, the paper compares two main types of DNNs, CNN and GRU used for disaggregation to understand their capabilities, and limitations for real-world commercial implementation. The publicly available energy dataset REDD [22] was used for this study. In this study, available NN architectures were individually improved and modified to bring them onto a common platform for comparison. The remainder of the paper is organized as follows: Section II provides a brief discussion of different NN architectures and applied disaggregation techniques. Section III provides a detailed description of the proposed approach, datasets, and the related techniques which were used for comparison. Section IV presents the results with a comprehensive discussion, and Section V concludes this work.

DNN Based Disaggregation Techniques

DNNs have been used in many ways in NILM applications. Various signal features such as steady states, transient states, and hybrid features are exercised in both regressions based, and classification based NN models. It has used different input to output mapping techniques including sequence to sequence and sequence to point. Moreover, DNN has been combined with other disaggregation techniques such as HMM and GSP.

Convolutional Neural Network based Approaches

CNN is the most used NN type in the NILM domain. It has been exercised in many ways for energy disaggregation and appliance classification. A disaggregation model was developed by combining Convolutional layers with Gated Linear Units [20]. Accuracy and the robustness of the model have further improved with the support of Residual blocks. The sliding window approach was adopted to learn temporal information while minimizing the outlier effect. One dimensional parallel convolutional layer is combined to make a non-symmetric autoencoder for disaggregation purposes [21]. The proposed model accepts a window of an aggregate signal as input and predicts the target appliance energy consumption signal window at the output layer. This regression-based sequence to sequence prediction model used liner activation as the activation function for output layer neurons for consumption prediction. However, this approach is limited to a single appliance prediction. The state change of an operating appliance creates a unique signature specific to that appliance. Active-reactive power variations at appliance switch ON-OFF events has used to create a power plot as CNN input for appliance classification [23]. It has tested 34 different events with the proposed model and 87% of the appliances were accurately classified.

The availability of temporal information for a CNN is limited to the width of the input window. A CNN based disaggregation model was developed with a tap delay to insert the recurrent property [24] into CNN based disaggregation model. A single CNN was divided into two parts and the output of the first section fed into the second section together with the original input to the first section. This will allow the model to learn the temporal relationship between timeslots beyond the length of the input window. Preserving temporal information has substantially improved the disaggregation accuracy of the proposed model. The increasing complexity of the activation signatures requires deeper CNN for accurate disaggregation. However, deeper CNN suffers from gradient explosion and vanishing within the model training phase. Hence, a new CNN model was introduced using residual units (ResNet), specially for complex activation signature disaggregation [25]. One of the key limitations with most of the NN based disaggregation approaches is the requirement of a separate NN model for each appliance. Hence, there are several initiatives to build a single module for multiple appliance disaggregation. One initiation was taken to construct a CNN modular Tree structure for iterative appliance energy disaggregation as a single model [25]. The root node of the Tree accepts the aggregate energy signal and filtered the assigned appliance consumption of the node and passes the residual energy signal to the child node. Each node recursively extracts appliance by appliance, and the balance will be considered as a new appliance. In addition to the Tree approach, a feasibility study has been conducted [26] to find CNN-based generic data-driven disaggregation model and it was able to find a few acceptable models. Moreover, CNN was combined with Variational Auto-Encoder (VAE) [27] to extract target appliance energy consumption from the aggregate signal. Multiple inputs were considered instead of a single input, for more effective disaggregation [28] using causal 1D CNN with current, active power, reactive power, and apparent power as inputs.

Recurrent Neural Networks based Approaches

Capturing and learning temporal information will enhance the accuracy of disaggregation performances. RNN and its variants have the capability of keeping memory within the NN with different degree of control capabilities. Hence, researchers have been using RNN and its variants for NILM. One of the research projects in the NILM domain used RNN for real-time energy disaggregation [30] for multi-state appliances. It used the sliding window approach by letting the aggregate energy signal sweep through the input window and extract all temporal information as much as NN can store.

LSTM is another powerful variant of RNN that has greater controllability over other NNs. Moreover, LSTM provides better resistance for gradient vanishing/exploring problem that is common in deeper RNNs. LSTM allows the user to control its memory function via gates, what information to be retained, what to remove, and what new information to be stored in the next timestamp. Ground breaking research presented the use of bi-directional LSTM NN for energy disaggregation with 100% accuracy for some of the appliances. The model has greatly enhanced its generalization capability by adding 50% of synthetic data including possible appliance combinations. It has used normalized mini batches of sizes 16 and 64 to speed up the training process and duration for convergence while minimizing the effect of always ON loads. It has confirmed that the use of temporal information with better control can achieve 100% disaggregation accuracy. Counter research [31] minimized the complexity of [30] by making the LSTM network unidirectional instead of bi-directional. This conversion was able to reduce the number of trainable hyperparameters from 1,264,977 to 486,261 that greatly reduces the computational complexity and memory requirement. However, the disaggregation performance of [31] slightly below compared to [30]. Another approach was taken by combining LSTM with CNN targeting two state appliance disaggregation [32]. The initial set of convolutional layers learns the hidden power patterns and LSTM preserve and learns the temporal information for improved disaggregation performances.

GRU can be considered as a miniaturized version of LSTM that have many similarities between them. GRU does not contain a separate forget gate as LSTM to clear previous memory explicitly. However, GRU contains a considerably less amount of trainable hyperparameters compared to LSTM. Hence, computational load and memory requirement for GRU is comparatively lesser than LSTM. Real time energy disaggregation model was developed using GRU specialized for commercial buildings [33]. Within the research, accuracy of GRU and LSTM models was compared against the degree of hyperparameter tuning and regularization. Results conclude that the overall performance of GRU is slightly better than LSTM. A single NN model for multiple appliance disaggregation was tried using GRU [34]. The model was trained and tested extensively using several publicly available energy datasets including REDD, REFIT, and UK-DALE to improve the generalization of the model. However, four separate NN models were developed for four separate appliances. The proposed model was able to achieve substantially improved generalization capability within the same appliance category.

In addition to CNN and RNN based disaggregation models, there were a set of other approaches available in the NILM domain. Autoencoder was another NN category tested, considering disaggregation as a de-noising process. Extracting the target appliance signal from the aggregate signal by filtering out other appliance energy consumption as noise components in the signal [31,35,36] is the key principle behind the use of dAEs. Causal networks are also considered for disaggregation, since maintaining causality is important to provide real time disaggregation data to the user. Causal Convolutional Neural Networks (CCNN) were used with multiple activation functions and multiple output blocks for better performance [37].

There were several performance indices used to measure the disaggregation performance including accuracy, precision, F-1 score, recall, mean squared error, mean absolute error for consumption estimation, and confusion matrix for appliance classification. The definitions of these can be found in [36].

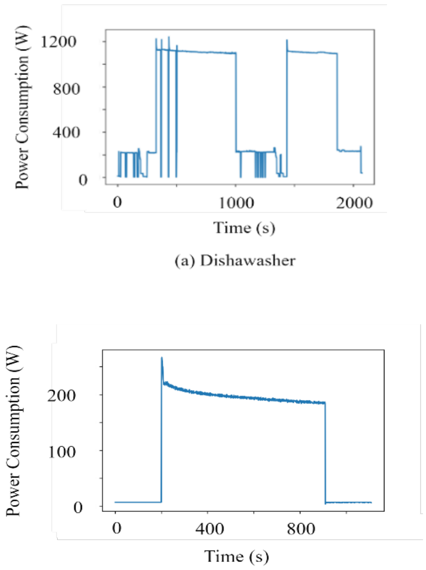
Methodology

This section presents the data pre-processing, the basis for appliance and their parameter selection, input-output mapping strategies, NN architectures, the use of the proposed model for energy disaggregation, and finally, the comparison schemes of disaggregated data.

Appliances Selection and Data Pre-Processing

The publicly available REDD [18] energy dataset was selected by considering the availability of a large volume of energy data, the number of houses, and common appliances. Moreover, REDD has been used by many researchers, and it will be easy to benchmark performance among studies. The refrigerator was selected as the base appliance for model testing and comparison, considering the volume of available training data and the simplicity of the appliance activation signature. Microwave oven and dishwasher were selected as the other two appliances to investigate the generalization capability of the model where the microwave oven has a simple and similar activation signature to the refrigerator, but dishwasher activation is very complex and of longer duration compared with the refrigerator. Figure 1 presents the activation signatures of the dishwasher and refrigerator.

Figure 1: Activation Signals of Dishwasher and Refrigerator



(b) Refrigerator

Usually, the energy dataset contains a common set of errors such as missing data points, data disordering, and outliers (i.e., spikes). Hence, it is essential to pre-process energy data prior to use in training and testing of the model. As the first step, all the data columns are rearranged in ascending timestamp order. Then after, all the data fields including the timestamp column, aggregate energy data column, and individual appliance energy data columns check for missing data. If the missing data length is less than 5 s data fields were forward filled with the last data value. The forward filling length should be less than the half of activation signal to minimize the data distortion. Hence, 5 s was calculated by analysing the shortest activation signature length of the microwave oven. If the missing data width is higher than 5 s, all corresponding data of all columns have been removed for the missing period. The outlier effect can be minimized by averaging nearby data points, but it will create nonviable operating states. Hence, averaging was not considered in data pre-processing.

Detailed analysis of the dataset found that some appliances behave in high sparse nature. Specially appliances such as a microwave oven that is rarely in switch ON mode compared to a complete day (i.e., 24 hours). This will badly affect the model training performance. Hence a well-known NILM tool kit called NILMTK[38] was used to extract the activation signatures from data fields. Thereafter, modified aggregated and appliance energy signals were created by concatenating extracted activation windows. Finally modified data fields were used to make normalized [38] mini bathes to reduce the model convergence time. Each mini batch contains a set of aggregate energy input windows and the respective output window of the target appliance.

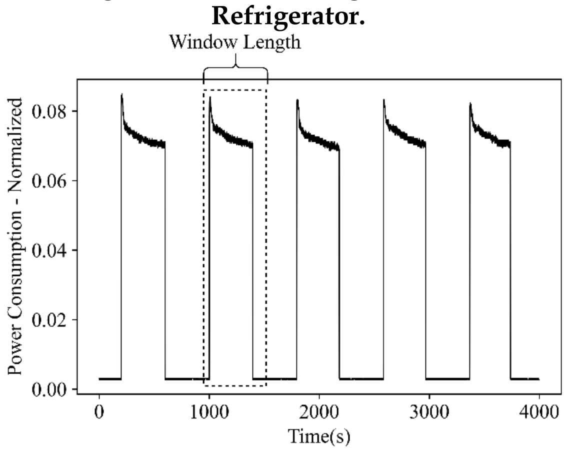
Window Selection and Input-Output Mapping

The performance of the disaggregation process depends on the quality and the information richness of the input data to the model. Hence, it is essential to capture the entire length of the activation signature at the input for better disaggregation accuracy. Therefore, it is required to analyse each appliance activation signature and set the input window length for the model slightly higher than the activation length. Table I presents the activation signature length and selected input window size for each appliance, and Figure 2 illustrates the input window arrangement for refrigerator.

Table 1: Activation Window Lengths of Appliances

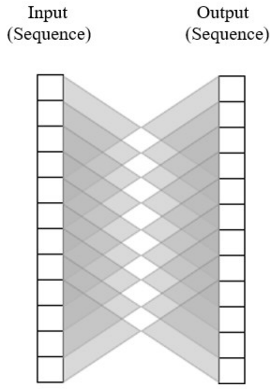
Appliance	Average Activation Signature Length (s)	Input window length(s)
Refrigerator	500	750
Microwave Oven	150	200
Dishwasher	2,000	2,500

Figure 2: Window Length Selection of Refrigerator.



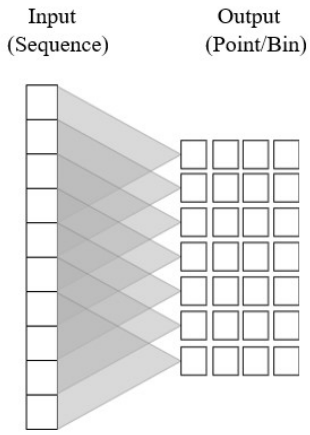
There are several input to output mapping techniques available in disaggregation studies. The two main types are Sequence to Sequence mapping and Sequence to Point mapping. In Seq to Seq mapping as illustrated in Figure 3, a window of aggregate energy signal map to a target appliance power consumption window of the same size as the input window. This is a regression-based approach that uses linear activation at the output layer neurons of the NN architecture.

Figure 3: An Illustration of Sequence-to-Sequence Mapping



An appliance can be defined as a finite state machine since most of them are operating at several distinct states such as on, off, high speed, and low speed. Hence, Seq to Point mapping was introduced to map the input aggregate energy window to one of the operating states at the output layer as illustrated in Figure 4. This is a classification-based approach that uses the Softmax activation function at output layer neurons. The Seq-Point mapping can overcome the effect of outliers that are commonly available in energy datasets.

Figure 4: An Illustration of Seq to Point Mapping



There are two subcategories of Seq to Point mapping named Hard Association and Soft Association. In hard association, the input window selects only one state (i.e., Bin) at the output layer among possible operating states.

Hard Association: In hard association, according to the predicted output value, it checks the distances to Bin centres and selects the closest Bin as the value of output. It can be modelled by assigning probability "1" for the closest Bin and assigning "0" for others as shown in (1), where p_{ij} indicates the probability that point i belongs to the Bin j and among k number of Bins [9].

$$p_{ij} = \begin{cases} 1, & if\ j = \arg\_min_k |cluster_{center_k} - point_i| \\ 0, & if\ otherwise \end{cases}$$

However, in some of the appliances such as microwave ovens, some of the states rarely occur and that state imbalance will adversely affect the training process, since some of the bins were not equally trained. Hence, a new mapping approach was adopted named soft association. In soft association, instead of selecting one bin, it assigns a probability for each bin according to the distance between the predicted point and bin centres, as explained below.

Soft Association

In soft association, instead of selecting a Bin, it assigns a probability for each Bin as per the distance to the Bin centers as given in (2) and (3), where p_{ij} indicates the probability of the point i belongs to the Bin j among k number of Bins and d_{ij} is the distance between cluster center j and point i [9]. Finally, the value of each Bin center is multiplied by the assigned probability to calculate the value of the predicted output point. The number of Bins per each appliance and values of Bin centers are presented in Table 2.

$$p_{ij} = \frac{\frac{1}{d_{ij}^2}}{\sum_k \frac{1}{d_{ik}^2}} \qquad (2)$$

$$d_{ij} = cluster\_center_j - point_i \qquad (3)$$

Table 2: Bins and Values of Bin Centers of Appliances

Appliance	Number of Bins	Values of Bin Centres
Refrigerator	4	4, 114, 166, 429
Microwave Oven	3	24,1522,1764
Dishwasher	5	10,410,223,750,1123

Neural Network Architecture

This comparison considered two types of NNs, that are CNN and GRU. CNN is better at extracting and learning appliance specific consumption patterns through related signal features and GRU can retain previous operating states of the appliance through its memory and understand the temporal information for consumption prediction. To provide common ground for a fair comparison, both NNs kept in the same depth (i.e., number of hidden layers) and same architecture except category-specific inherited properties. Table III and IV present the architecture of each NN.

Table 3: Convolutional Neural Network Architecture

Layer Type	Hyper Parameters	Activation Function
Convolutional 1D	8, 3x3 Kernels	
Convolutional 1D	16, 3x3 Kernels	
Convolutional 1D	32, 3x3 Kernels	
Convolutional 1D	64, 3x3 Kernels	
Max Pooling 1D	2 Pool Size	
Flatten		
Dense	100 Neurons	ReLU
Dropout	0.5 Probability	
Dense	Number of Bins	Softmax

Table 4: GRU Neural Network Architectures

Layer Type	Hyper Parameters	Activation Function
GRU	8 Units	
GRU	16 Units	
GRU	32 Units	
GRU	64 Units	
Flatten		
Dense	100 Neurons	ReLU
Dropout	0.5 Probability	
Dence	Number of Bins	Softmax

Disaggregation Process

It is better to have all possible appliance combinations present in aggregate signal windows used for model training to increase the model generalization capability. However, within the available training data, all possible combinations may not be available. Hence, actual activation signals were combined artificially and created synthetic data with different appliance combinations. Proposed models were trained using mini batches with the combination of a 25:75 ratio in synthetic to actual data.

Prepared mini batches were divided for training, validation, and testing in a 70:20:10 ratio. A sliding window approach was adopted where sequential windows from mini batch fed into the NN. It allows NN to learn temporal information much faster. Several NN initialization methods experimented. However, it was not evident a considerable contribution from any of them for faster model convergence. Finally, random initialization was selected considering its simplicity. After experimenting with several optimizers, the

Adam optimizer was selected considering its unbiased nature towards appliances.

Several popular performance indices within the NILM domain were considered for performance comparison including accuracy, precision, recall, and F1 measure. Intel® Core i7 processor with 32GB RAM and Nvidia® GPU with 2GB memory were used for all neural network modelling, training, and testing. Python programming language was used with Tensorflow® and Keras® (at the backend) for modelling the CNN and GRU architectures.

Results

In this study, comprehensive energy disaggregation testing was carried out with two types of NNs, CNN and GRU. Appliances including refrigerator, microwave oven, and dishwasher were considered for model testing. Table X presented the results of an average of 25 epochs of each appliance against performance indices including accuracy, precision, recall, and F1 for three types of test categories, Cat A, B, and C. Three test categories are explained in Table 5.

Table 5: Test Categories

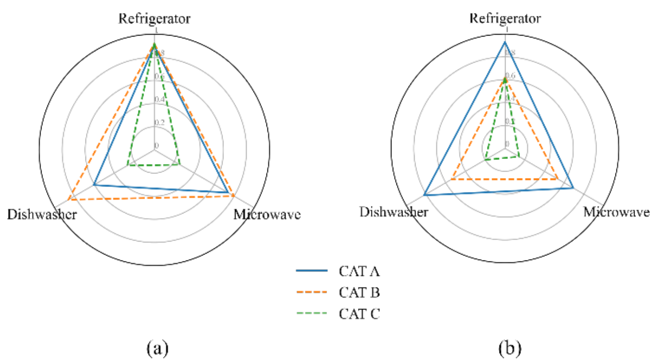
Test Category	Trained House	Tested House
CAT A -Seen House	House 1	House 1
CAT B- Unseen House 1	House 1	House 2
CAT C -Unseen House 2	House 1	House 3

Table 6: Performances of CNN and GRU NNs

Test Category	Appliance	Accuracy		F1		Recall		Precision	
		CNN	GRU	CNN	GRU	CNN	GRU	CNN	GRU
CAT A	Refrigerator	0.9	0.93	0.4	0.399	0.25	0.249	0.991	0.993
	Microwave Oven	0.919	0.621	0.489	0.471	0.324	0.31	0.993	0.995
	Dishwasher	0.927	0.62	0.328	0.296	0.196	0.175	0.996	0.996
CAT B	Refrigerator	0.74	0.693	0.399	0.399	0.249	0.249	0.991	0.995
	Microwave Oven	0.8	0.538	0.498	0.465	0.332	0.308	0.99	0.992
	Dishwasher	0.256	0.144	0.323	0.242	0.193	0.139	0.992	0.994
CAT C	Refrigerator	0.607	0.821	0.399	0.395	0.249	0.246	0.993	0.993
	Microwave Oven	0.861	0.542	0.489	0.469	0.324	0.311	0.992	0.96
	Dishwasher	0.271	0.2	0.314	0.303	0.186	0.179	0.996	0.992

As per the result presented in Table VI, considering all performance indices for all appliances under three test categories, CNN performs slightly better than GRU. Among the four performance indices presented above, accuracy is the most important performance index to evaluate disaggregation performances. Hence, from here onwards, accuracy will be used for performance analysis and comparison.

Figure 5. Performance Comparison between (a) CNN and (b) GRU.



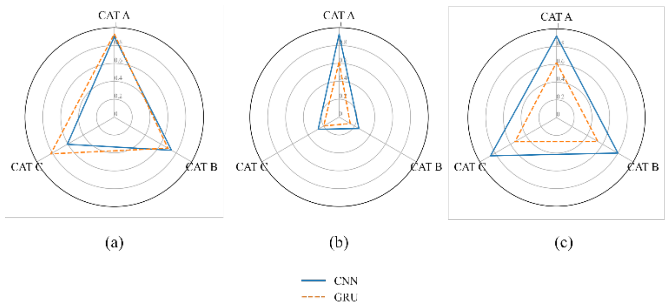
Accuracy of the disaggregation prediction compared between CNN and GRU for all appliances under three test categories is presented in Figure 5. Graphs for both CNN and GRU followed the same shape. Hence, both NNs treated without any bias to all appliances in three test categories. In both NN types, the dishwasher performed slightly lower than other appliances. There are two reasons identified for this performance drop. The activation signature of the dishwasher is lengthier and more complicated compared to the other two appliances. This experiment used simple shallow NNs for disaggregation prediction. When activation signatures are getting more complicated, it is required to have more deeper NNs for accurate disaggregation. Hence, the dishwasher couldn't perform as same as the other two appliances. However, by equipping more deeper NN, disaggregation performances of the dishwasher could further improve. The identified second reason was, that the number of training samples (i.e., training data volume) for the dishwasher is comparatively lesser than the other two other appliances as presented in Table 7. This adversely affects the model training, since no adequate amount of data to learn all features related to dishwasher energy consumption patterns. This can be overcome by providing more training data during the training phase.

Table 7: Training Data Volume for each Appliance Model Training Phase

Appliance	Training Data Volume
Refrigerator	266,440
Microwave Oven	20,298
Dishwasher	13,282

Appliances wise disaggregation performance was analysed as presented in Figure 6. The performance of CAT B and C is lower than CAT A for all appliances. This is obvious since CAT A was trained and tested from the same house data, but the other two categories of trained and tested houses are different. Hence, in the testing phase, CAT B and C had to identify appliance consumption patterns that they did not see in the training phase. However, refrigerator and microwave oven perform well in CAT B and C than the dishwasher. This is also because of lesser training data volume and the complex signature of the dishwasher. Furthermore, refrigerator and microwave oven presented a greater generalization with the proposed models. Detailed analysis shows that except CAT C of the refrigerator, and all other test categories of all appliances, CNN performs better than GRU. Hence, CNN has better generalization capability than GRU.

Figure 6: Performance Comparison between Test Categories (a) Refrigerator, (b) Microwave oven, (c) Dishwasher



In addition to the accuracy based NN comparison, it is essential to assess the time taken for energy disaggregation by each NN. When implementing proposed models as commercial solutions to run in real-time, the speed of disaggregation became critical. Hence time taken for one disaggregation round (i.e., for a single epoch) was calculated by averaging individual epoch durations for test category A and presented in Table 8.

Table 8: Training Data Volume for each Appliance Model Training Phase

	Time Taken per Epoch per Mini Batch (ms)		
	Refrigerator	**Microwave Oven**	**Dishwasher**
CNN	12.87	8.62	53.52
GRU	617.76	129.31	255.35

The duration of CNN is well below compared with GRU duration. This is due to the additional processing weight of GRU keeping memory within the cell (i.e., backpropagation through time). Moreover, results show that microwave oven recorded the shortest duration while dishwasher shows the longest duration. This is directly related to the length of the activation signature and complexity vs simplicity of the activation signature.

Conclusions

Energy conservative behaviour of domestic users begins with access to individual appliance consumption statistics. AI based NILM approaches allow the user to collect appliance level power consumption data with minimum interactions with individual appliances and without complicated mathematical calculations or manual feature extractions. Two NN categories were analysed for NILM including CNN and GRU a member of the RNN family against performance indices for accuracy, recall, precision, and F1 score. CNN performs slightly above GRU overall. Both GRU and CNN follow a similar pattern in accuracy measures for all appliances under three test categories, confirming there is no bias of NN towards any appliance. The complexity of the activation signature plays a critical role in NILM. Appliances with simple signatures perform better than complex signature appliances in NILM. It is required to have a deeper NN to deal with complex signatures sacrificing more computational capacity. Moreover, the accuracy of the prediction increases with the availability of training data volume. Seen house category for all appliances has performed better than the unseen house categories, since it has witnessed the all-appliance signatures within the training phase. GRU has taken a longer duration than CNN for one training epoch due to its memory update and backpropagation through time. CNN is the lightweight and faster NN that is most suitable for NILM applications than GRU, specially to implement as a commercial solution.

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