Transformer for Non-Intrusive Load Monitoring: Complexity Reduction and Transferability

Lingxiao Wang, Shiwen Mao, *Fellow, IEEE*, and R. Mark Nelms, *Fellow, IEEE*

***Abstract*—Non-Intrusive Load Monitoring (NILM) is to obtain individual appliance's electricity consumption from aggregated smart meter data. In this paper, we propose a Middle Window Transformer model, termed *Midformer*, for NILM. Existing models are limited by high computational complexity, dependency on data, and poor transferability. In Midformer, we first exploit patch-wise embedding to shorten the input length, and then reduce the size of queries in the attention layer by only using global attention on a few selected input locations at the center of the window to capture the global context. The cyclically shifted window technique is used to preserve connection across patches. We also follow the pre-training and fine-tuning paradigm to relieve the dependency on data, reduce the computation in modeling training, and enhance transferability of the model to unknown tasks and domains. Our experimental study using two real-world datasets demonstrates the superior performance and transferability of Midformer over three baseline models.**

***Index Terms*—Non-intrusive load monitoring (NILM), Transformer, Attention, Transferability, Smart home.**

I. Introduction

The recent advances in the Internet of Things (IoT) allow the deployment of uniquely identifiable objects that are organized in an Internet-like structure to enable smart homes to monitor, control, and manage house appliances [1]. The communication paths constructed by the IoT integrate smart meters, home appliances, and renewable energy, in a Home Energy Management System (HEMSs) [2], [3]. With more and more IoT-enabled technologies being developed and deployed, the HEMS system will become more sustainable, more resilient, and more energy efficient [4].

One important application of the IoT in HEMSs is load monitoring. The built-in sensors in appliances provide individual appliance's energy consumption information to the HEMS in realtime, which can be analyzed to optimize the energy usage and achieve energy savings. However, there are several practical issues that need to be addressed. First of all, electrical appliances typically last up to decades. As a result, a household typically include both old and new generations of appliances. The legacy appliances may not be equipped with smart sensors and their electricity consumption data is usually hard to measure. Second, the cost of installing sensors to legacy appliances could be high, including both the sensor and installation cost, as well as the power usage cost. Third, consumers are more and more concerned about their privacy; they may not be willing to share the information about their appliances' power consumption.

Non-Intrusive Load Monitoring (NILM), which is to identify individual appliance's electricity consumption from the given aggregated smart meter data, provides a useful solution to the above problems [5]. Recently, deep neural networks (DNNs), such as Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs), have been shown effective to address the NILM problem. Since 2017, the Transformer [6] and its variants have dominated the field of natural language process (NLP), achieving superior performance for tasks such as language translation, text analytics, smart assistants, and so on. This is largely due to Transformer's capability of using the attention mechanism to capture the long-range dependency in sequential data. For computer vision (CV) tasks, the Vision Transformer (ViT) [7] has been shown to outperform the popular CNN model. In our recent work [8], a deep spatio-temporal attention approach was developed to forecast the temperature of stored grain using meteorological data. Such successes in NLP, CV, and other fields have attracted researchers to investigate Transformer's application to the NILM problem.

Although some recent preliminary studies have demonstrated the high potential of Transformer for NILM [9], [10], there are still many challenges remain to be addressed. First is the tradeoff between computational complexity and the ability to track long range dependency in energy consumption data, which usually contains rich daily, seasonal, and even annual patterns. The self-attention mechanism is the core of Transformer, which has a quadratic time complexity with regard to the input sequence length [11]. Low complexity models are thus desirable to allow longer input sequences. Second is the dependency on data. Like most Deep Learning (DL) models, Transformer requires a large amount of high quality labeled data for training, specifically, each individual appliance's power consumption data. The cost of data collection, e.g., submetering, could be high. In addition, many users are unwilling to share their appliance's information due to concern of privacy breach. Third is the generalization or transferability of the well trained Transformer model. The existing Transformer-based NILM methods are trained and tested on the same dataset, or assume the training and testing sets share similar data distribution. The transferability of the models have not been fully investigated, including testing across different appliances and/or across different datasets. NILM models with strong transferability are useful to achieve accurate predictions for different, unseen houses, different

This work is supported in part by the NSF under Grants DMS-1736470 and CNS-2107190, and by the Wireless Engineering Research and Education Center at Auburn University, Auburn, AL, USA.

L. Wang, S. Mao, and R.M. Nelms are with the Department of Electrical and Computer Engineering, Auburn University, Auburn, AL 36849-5201, USA. Email: lzw0039@auburn.edu, smao@ieee.org, nelmsrm@auburn.edu.

DOI: 10.1109/JIOT.2022.3163347

models or brands of appliances, various aging degrees of electronic circuits, and different residents daily habits and usage behavior [2].

In this paper, we propose a **Mid**dle Window Trans**former** model, termed Midformer, for NILM, which incorporates several novel designs and follows the pre-training and fine-tuning paradigm to address the above problems. To deal with the computational complexity issue, Midformer is designed as a more efficient Transformer variant tailored to the characteristics of the NILM problem. Specifically, we utilize patch-wise attention in Midformer, which reduces the input length compared to point-wise attention used in existing models [9], [10]. We further apply the cyclically shifted window technique to increase the receptive filed. The drawback of patch-wise attention is that it ignores the connection across patches. In Midformer, we feed both cyclically shifted input and the original input into the attention layer to preserve the connection across patches. To reduce computation, we only calculate full attention using the middle range of the input, instead of using the entire input. This allows Midformer to focus on the middle range of the input and achieve a linear time complexity with respect to the input length (i.e., the window size).

To address the transferability issue and reduce the dependency on data, we follow the pre-training and fine-tuning paradigm. First, we pre-train multiple transformers (for different appliances) by using one dataset. Then we test the performance of the trained models on unseen data in the same dataset. Next, we examine the relationship among different appliances, i.e., could a model pre-trained using one appliance's data in a house be used to predict the power usage of another appliance in another house? The authors in [12] used the model learned from washing machine data to predict the power consumption of other appliances. In this paper, we obtain the pre-trained model (including CNN, RNN, Transformer, and the proposed Midformer) for five appliances (including kettle, dishwasher, fridge, washing machine, and microwave). We then fine-tune and test the pre-trained model on a different dataset including the same and different appliances' data. With this approach, models do not need to be retrained from scratch for unknown houses and unseen appliances, and can quickly adapt to new tasks with few-shot fine-tuning due to the well initialized parameters in the pre-trained models. This way, the computation in modeling training can be reduced and the dependency on data can be relieved.

We evaluate the performance of the proposed Midformer model using two real-world datasets and compare it with three baseline models including CNN, RNN, and Transformer. Our experimental study demonstrates the superior performance and great transferability of the proposed Midformer model for NILM problems over the state-of-the-art baseline models.

We organize the remainder of this paper as fellows. We introduce related work in Section II. In Section III, we formulate the NILM problem and introduces the preliminaries of Transformers. In Section IV, we present the proposed transformer method Midformer. We present the datasets and experiment setup, and discuss the experimental study in Section V. Finally, Section VI concludes this paper.

II. Related Work

A. Non-intrusive Load Monitoring Models

In the literature, many prior studies have developed approaches for solving the NILM problem, which can be mainly divided into two categories: (i) unsupervised learning, and (ii) supervised learning methods. In this section, we will briefly introduce the existing solutions for NILM; more detailed reviews of the different approaches applied to solving NILM can be found in [5], [13], [14].

1) Unsupervised Learning: Unsupervised learning has the unique strength of not requiring labeled data. The additive factorial hidden Markov model (AFHMM) is one of the most widely used unsupervised learning approaches for NILM [15]–[18], which converts time series data into Hidden-Markov Models and Bayesian models to infer the possible states of different appliances. Another method of unsupervised learning approach is the Graph Signal Processing (GSP) based method, which has also been shown to be quite effective for NILM [19], [20]. The main drawbacks of these methods is that the prior domain knowledge needs to be provided, and such schemes may not perform well for solving problems that have a large number of appliances [12].

2) Supervised Learning: Supervised learning aims to learn a function, which maps an input to an output, from given input-output examples, i.e., labeled data. In the literature, various supervised learning methods have been applied to solving the NILM problem, such as Support Vector Machine [21], Decision Tress [22], K-Nearest Neighbours (k-NN) [23], and so forth. Recent works in this area demonstrate the promise of entirely deep learning approaches, such as Convolutional Neural Networks (CNNs) [24]–[27], Long Short-Term Memory (LSTM) or its variant Gated Recurrent Units (GRUs) [28]–[31], and denoising autoencoder [32], [33]. The main limitation of supervised learning (machine learning) method is that it requires large amounts of high quality training data. Such approaches usually require high computational power and storage capacity.

B. Transfer Learning for NILM

Most of the approaches applied to the NILM problem are carried out on the same data domain, which means the model is trained and tested using the same appliance's data in the same dataset. Very few previous studies have addressed the study of generalizability of the NILM models, also referred to as the transferability of the pre-trained models. For example, in [34], Murray et al. trained two different networks based on CNNs and RNNs, respectively, by using one of the three datasets and verify the models' transferability as well as generalization through the other datasets. However, the stability of the trained models is unsatisfactory due to the different data distributions in different databases, which lead to the poor domain adaptation performance.

To address this problem, D'Incecco, Squartini, and Zhong in [12] pre-trained their sequence-to-point (seq2point) learning model using the washing machine data in one specific dataset, and then tested their pre-trained model on data of different appliances in different datasets. Fine-tuning, which is to train

the pre-trained model using a small amount of examples from the testing dataset [2], was applied to adapt the pre-trained model to the difference between the different training and testing domains. However, the distribution of data used in fine-tuning was quite different from that of the tested house data, which led to the *negative transfer* effect. The generative adversarial networks (GANs) model has been applied to address the domain adaptation problem in NILM as well [35], [36], which was to train the feature generator and the domain discriminator in the adversarial manner. The limitation of this method is that training GANs requires finding a Nash equilibrium of a non-convex game with continuous high-dimensional parameters, which could fail to converge [37], [38]. Our previous work [2] developed a meta-learning based approach and an ensemble learning based approach that require fewer new data for adaptation, and can quickly adapt to new NILM tasks. However, we only explored the transferability between different datasets of same appliance in [2].

C. Transformer-based NILM Models

Motivated by the success of the Transformer architecture in many domains, most importantly in Natural Language Processing (NLP) [6], the self-attention[1] based Transformer has recently been proposed for NILM. The recent works [9], [10] both applied the attention mechanism to the feature maps extracted by CNNs to solve NILM tasks. The main drawback of these preliminary studies is that the computational complexity of self-attention grows quadratically with window (i.e., input) size, which could become a serious issue if the fixed window size is large. Moreover, the generalization performance of these models have not been verified through different datasets or appliances.

III. Problem Statement

A. The NILM Problem

Consider a given collection of J time series $\{y_1(t),\ y_2(t),\ ...,\ y_J(t)\}_{t=1}^{T}$ that record the energy consumption of the J appliances in a house over a period of time T; $\{y_j(t)\}_{t=1}^{T}$ represents the power consumption of the jth appliance in the house. The aggregate power consumption $x(t)$ of the house at time t is calculated as follows.

$$x(t) = \sum_{j=1}^{J} y_j(t) + e(t), \tag{1}$$

where $e(t)$ is the measurement noise at time t. The NILM problem is to estimate the power consumption of an individual appliance from the given aggregate power consumption of the entire house. It is also called energy disaggregation since the goal is to separate the energy consumption measured at the aggregate level to that of individual appliances. It is non-intrusive since only the aggregate measurement is needed; and there is no need for submetering.

In NILM algorithms, to better handle the long time series data, usually a sliding/rolling window setting is adopted over the time series with a fixed window size, denoted by W, where the sliding/rolling step size is one. Rather than predicting a full window size of outputs, the NILM models often target at one single time instance (e.g., the middle point of the window) to avoid redundant computation. This approach is termed sequence-to-point (s2p) learning [24]. Therefore, given input data of total power consumption measurements over a window of size W, i.e., $\tilde{\mathbf{x}} = \{x(1), x(2), ..., x(W)\}$, the learning algorithm will compute output $\tilde{y}_j(\lceil W/2 \rceil)$, for all j.

[1]"An attention mechanism relating different positions of a single sequence in order to compute a representation of the sequence [6]."

B. Transformer and Multi-head Self-attention Mechanism

The Transformer model is based on the attention mechanism to significantly enhance the performance of deep learning, which computes the representation of a sequence by attending to information at different positions from different representation subspaces [6], [39]. The main idea of this mechanism is to learn an alignment between each element in the sequence and others to decide which part of the sequence should be paid attention to [40].

For a given input sequence $\mathbf{I} \in \mathbb{R}^{W \times d_{model}}$, where d_{model} is the dimension of each data sample (i.e., length of the encoding vector), self-attention first transforms the input sequence into three matrices with three learnable weights. These three matrices are called queries, keys, and values, respectively, and they have the same depth of dimension d. Next the scaled dot-product is computed, which is given by:

$$\text{Attention}(\mathbf{Q}, \mathbf{K}, \mathbf{V}) = \text{softmax}\left(\frac{\mathbf{Q}\mathbf{K}^T}{\sqrt{d}}\right)\mathbf{V}, \tag{2}$$

where $\mathbf{Q} = \mathbf{I}\mathbf{W}^Q$, $\mathbf{K} = \mathbf{I}\mathbf{W}^K$, and $\mathbf{V} = \mathbf{I}\mathbf{W}^V$, and $\mathbf{W}^Q \in \mathbb{R}^{d_{model} \times d}$, $\mathbf{W}^K \in \mathbb{R}^{d_{model} \times d}$, and $\mathbf{W}^V \in \mathbb{R}^{d_{model} \times d}$ are all trainable parameters that are used to map the input $\mathbf{I}$ into the three matrices $\mathbf{Q}$, $\mathbf{K}$, and $\mathbf{V}$. The attention function (2) is similar to non-local means, which can be described as mapping a query and a set of key-value pairs to an output [6]. The weighted sum of the values is computed as the output of attention, where the weight is determined by the softmax score of the query with the corresponding key.

In the Transformer model, the attention processor is also called attention head. Multi-head Self-attention computes the self-attention score function describe in (2) on H different linear projections of queries, keys, and values in parallel. Then the results are concatenated as follows.

$$\text{MultiHead}(\mathbf{I}) = \text{Concat}\left(\sum_{i=1}^{H} \text{Attention}(\mathbf{Q_i}, \mathbf{K_i}, \mathbf{V_i})\right), \tag{3}$$

where $\mathbf{Q_i} = \mathbf{I}\mathbf{W_i}^Q$, $\mathbf{K_i} = \mathbf{I}\mathbf{W_i}^K$, and $\mathbf{V_i} = \mathbf{I}\mathbf{W_i}^V$. The dimension of the learning parameters $\mathbf{W_i}^Q$, $\mathbf{W_i}^K$, and $\mathbf{W_i}^V$ is $d_{model} \times d_i$, where $d_i = d/H$. By combining several similar attention results, the attention will have stronger power of discrimination.

IV. Proposed Middle Window Transformer Approach

In this section, we introduce our proposed Transformer-based approach for NILM problems, which is termed middle

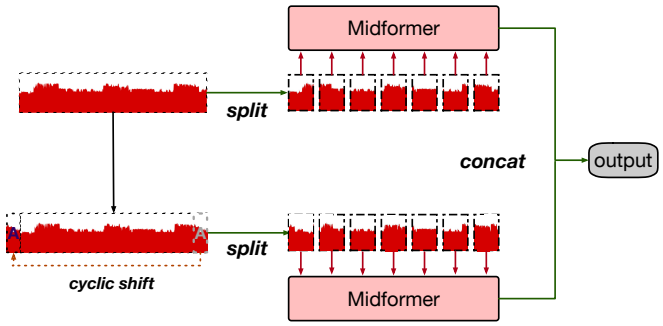
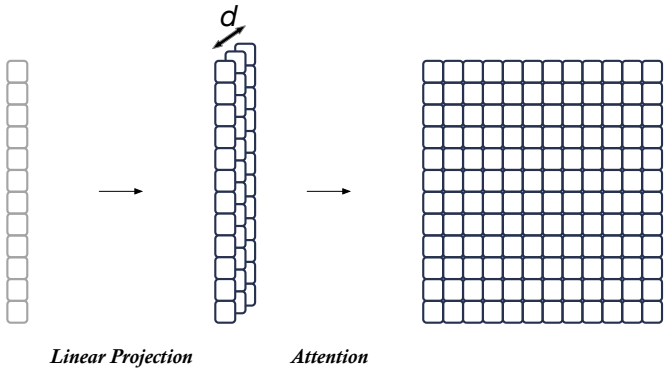
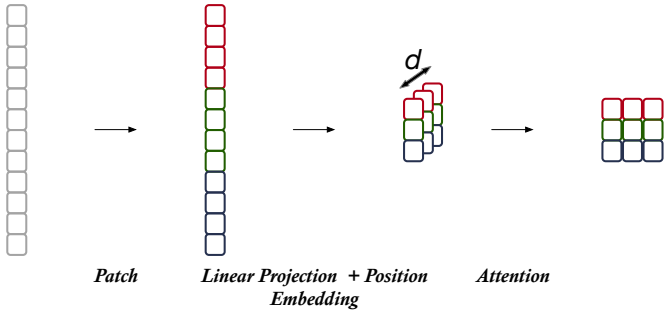


Fig. 1: Architecture of the proposed Transformer-based approach, Midformer, to NILM.



(a) The global full self-attention.



(b) Attention after splitting the input into small patches.

Fig. 2: Comparing the point-wise and the patch-wise attention pattern.

window transformer (Midformer). Fig. 1 illustrates the overall architecture, which consists of four main parts, including (i) patch splitting and initializing, (ii) cyclic shift window, (iii) Transformer layers, and (iv) concatenation. Our intuition of designing this approach is to utilize the Transformer's attention ability to model the long range dependency in the energy consumption data, while reducing the computational cost.

The existing methods [9], [10] exploit the attention mechanism for NILM by combining CNNs with forms of self-attention. They first extract the feature map from input data by using convolutional layers. The extracted feature map is then fed into the Transformer layers. They both adopt global full self-attention in their models, which has a computational complexity that is quadratic to the size of feature map. For efficient modeling and computation, we leverage the technique proposed in the Vision Transformer (ViT) for image classification tasks [7], which reduces the context length by partitioning images into small patches and using the patches as input to the Transformer layers. A comparison of the existing approach and that adopted in this paper is presented in Fig. 2. In particular, Fig. 2(a) shows the original point-wise attention projection method used in existing NILM works [9], [10], while Fig. 2(b) illustrates the patch-wise attention projection method adopted in this paper. As shown in Fig. 2(a), when creating the attention matrix, the input will first be mapped into a space of depth d, which will then be used by the attention mechanism to calculate the attention matrix. The length and width of the attention matrix are the same as the depth of the space. From the comparison figure, we can visually see that the patch-wise attention incurs significantly less computation than the point-wise attention as the dimension of the attention matrix becomes much smaller.

A. Patch Splitting and Initialization

In the proposed Midformer model, the input $\mathbf{I} \in \mathbb{R}^{W \times d_{model}}$ is first split into a sequence of non-overlapping patches of fixed-size $\{\mathbf{I}_1, \mathbf{I}_2, ..., \mathbf{I}_k\}$, where $\mathbf{I}_i \in \mathbb{R}^{W/k \times d}$, for $1 \leq i \leq k$, and k is the number of patches. Each patch contains W/k samples, and is fed into a neuron network to be projected into a d-dimension vector. Different from [9], [10], before the input data is passed into the Transformer blocks, we do not need the convolutional layers to extract the feature map and increase the hidden size of the input sequence. This part of essential operation is replaced by individual neuron networks that project the patches. We also add position embedding to the projection to maintain position information in the data. The output of this projection is referred as patch embeddings.

B. Window Shifting

The patch-wise self-attention splits the input series of samples into non-overlap patches. However, this approach breaks the data correlation at patch boundaries and ignores the connection across patches, which limit its modeling power. In order to capture the connection across patches while still maintaining the computational efficiency of non-overlapping patches, we apply the shifted window technique to broaden the receptive field, which is inspired by [41]. As illustrated in Fig. 1, we cyclically shift the input $\mathbf{I} \in \mathbb{R}^{W \times d_{model}}$ to the right for $W/(2k)$ positions (i.e., half of the patch size); the right-most half-patch of samples are moved to the left-most part of the window. The patches obtained from the cyclically shifted window of data are also fed into patch embeddings as well, to create a patch-wise feature map as shown in Fig. 1.

C. Transformer Layers

The two feature maps created by patch embeddings are then fed into the Transformer layers. We equally split the H heads into two parallel groups, where each group has $H/2$ heads (assume that H is an even number). One group accepts the

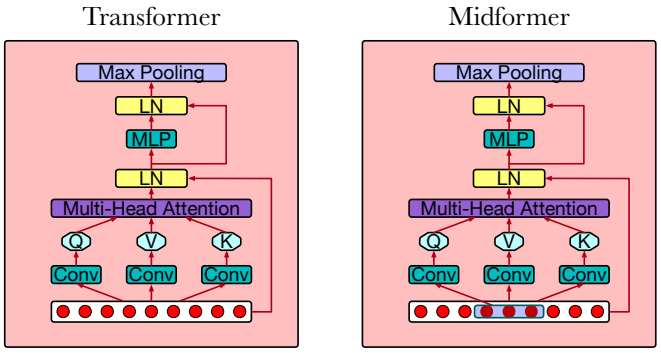


Fig. 3: Comparison of Transformer and the proposed Midformer approach.

feature map created from the original input, and the other group accepts the feature map created from the shifted input.

We follow the Transformer layer designed in [6], which consists of a multi-head attention layer and multi-layer perception (MLP) layer. A LayerNorm (LN) layer is applied after each attention layer and the MLP layer. A residual connection is used from the input to the first LN layer, and from the first LN layer to the second LN layer. The architecture of the original Transformer model is shown in the left plot in Fig. 3.

We further enhance the existing Transformer layer and propose the **Mid**dle Window Trans**former** (Midformer) layer, to achieve reduced computation complexity. The idea is simple: we only apply global attention on N (e.g., $N = 3$) input patches in the middle range of the window as queries, which is illustrated in the right plot in Fig. 3. The reason why we reduce the the number of queries is that, most NILM models (e.g., s2p [12]) only predict the appliance's power usage at the center position of the window. The middle range area of the window is where we should focus on. By reducing the number of queries, the complexity of the attention mechanism can be greatly reduced. It is worth noting that only the number of queries is reduced here, and the number of key-value pairs remains unchanged, which is fundamentally different from simply using a smaller window size W and then calculating the full attention. This technique contributes to the class of position-based sparse attention schemes, which reduce the required computations by limiting the number of query-key pairs that each query attends to [42].

D. Concatenation

Finally, an MLP (i.e., a fully connected layer) is utilized to concatenate the outputs of the two groups of Transformer blocks. The final MLP would restore the concatenated feature maps to the desired output size, which is one for NILM problems.

E. Computational Complexity Analysis

Supposing each input's dimension is $W \times d_{model}$, the patch size is W/k, the learnable parameter's dimension is $d_{model} \times d$, and the number of queries used in the Midformer layer is N. The computational complexity of the global Multi-head Self-attention module in each layer is $\mathcal{O}\left(W^2 \cdot d\right)$. The high cost of computing the global limits its ability to handle the usually large window sizes in NILM problems. However, with the proposed Midformer model, the computational complexity of the Multi-head Self-attention module is reduced to $\mathcal{O}\left(N/k \cdot W \cdot d\right)$. In the Midformer design, both N and k are set proportional to the window size W (e.g., $k = W/9$ and $N = k/3 = W/27$ in our experiments). Therefore, the computational complexity of Midformer is now linear to the window size W.

V. Experimental Study

In this section, we introduce the datasets and the system configuration used in our experiments to evaluate the performance of the proposed Transformer model. We then present our experimental study of the proposed model and compare it with three baseline models.

A. Datasets

We use two real-world datasets, the REFIT dataset [43] and the UKDALE dataset [44] to evaluate the performance of the proposed energy disaggregation method. The REFIT and UK-DALE datasets are both recorded in England. They both provide house-level aggregate energy consumption as well as individual appliances' power consumption data. In particular, the REFIT dataset consists of data from 20 households. Both the aggregate and appliance levels' data were recorded every 8 seconds from September 2013 to July 2015. The UKDALE dataset includes data from five houses. Each house's aggregated energy consumption was recorded every 1 or 6 seconds, and the appliance level data was measured every 6 seconds. In order to be consistent with data in different datasets, the aggregate level and appliance level data are down-sampled to 8 seconds. Standard score normalization is applied in data preprocessing; each sample x in the dataset is normalized as $\hat{x} = (x - \bar{x})/S$, where $\bar{x}$ is the sample mean and S is the sample standard deviation. We follow the approach in [12] to set the sample mean and sample standard deviation values for each appliance.

Following the approach in our recent work [2], for pre-training, we use a large-scale NILM dataset: i.e., the REFIT dataset. Specifically, we use the data from three houses as the pre-training set and the data from two other houses as the testing set for each appliance. The specific houses used and the amount of data from REFIT used to pre-train the model are summarized in Table I. We then use the UKDALE dataset to evaluate the generalization of the models. We use only a small part of the data in House 2 of the UKDALE dataset to fine-tune the pre-trained model and the rest of the unseen data of House 2 to test the performance of the fine-tuned pre-trained model. There is no overlap between the testing data and the fine-tuning data. The detailed information of the house and data from the UKDALE dataset used in our experiment is summarized in Table II.

TABLE I: Appliances and Houses Used in the REFIT Dataset [43]

	Training and validation dataset		
Appliances	House	Time period	Samples (M)
Kettle	5, 7, 13	2013-09-26 to 2015-07-08	18.91
Dishwasher	4, 10, 12	2014-03-07 to 2015-07-08	19.36
Fridge	2, 5, 12	2013-09-17 to 2015-07-08	13.28
Washing Machine	5, 7, 18	2013-09-17 to 2015-07-08	19.80
Microwave	5, 7, 18	2013-09-26 to 2015-07-08	19.80
	Testing dataset		
Appliances	House	Time period	Samples (M)
Kettle	9	2013-12-17 to 2015-07-08	6.17
	20	2014-03-20 to 2015-06-23	5.17
Dishwasher	9	2013-12-17 to 2015-07-08	6.17
	16	2014-03-10 to 2015-07-08	5.72
Fridge	9	2013-12-17 to 2015-07-08	6.17
	15	2013-12-17 to 2015-07-08	6.22
Washing Machine	15	2013-12-17 to 2015-07-08	6.22
	17	2014-03-06 to 2015-06-19	5.43
Microwave	17	2014-03-06 to 2015-06-19	5.43
	19	2014-03-06 to 2015-06-20	5.62

TABLE II: Appliances and Houses Used in the UKDALE Dataset [44]

	Fine-tuning dataset		
Appliances	House	Time period	Samples (M)
Kettle, Dishwasher, Fridge, Washing Machine, Microwave	2	2013-5-20 to 2013-5-29	0.108
	Testing dataset		
Appliances	House	Time period	Samples (M)
Kettle, Dishwasher, Fridge, Washing Machine, Microwave	2	2013-5-30 to 2013-10-10	1.592

B. Model and Experimental Setup

Next we introduce the experiment setup and the models used to address the NILM problem. The following three baseline models are evaluated for comparison purpose.

- Sequence-to-point (s2p [12]): this baseline model uses the same structure of sequence-to-point method as in [12].
- Bidirectional Gated Recurrent Units (Bi-GRU) [30]: this baseline model utilizes Bi-GRU, rather than LSTM, to reduce the amount of model parameters while maintaining a similar performance as the RNN model.
- Transformer (Transformer) [6]: this is the traditional Transformer model. It has the same hyper-parameters as the Midformer model proposed in this paper, which are summarized in Table III.

Note that comparisons between the s2p model and other traditional machine leaning methods have been presented in [12], including AFHMM, RNN, sep2sep, GRU, etc., where the s2p model achieves the best performance. Therefore we choose s2p as a benchmark scheme in this paper.

TABLE III: Hyper-parameter Setting of Midformer

Hyper-parameter	Value
Window size	99 297 495 693
Batch size	100
Adam	0.001
Maximum pre-training epochs	50
Maximum fine-tuning epochs	10
Number of heads	8
Number of layers	2 to 4
Number of patches	3 9 11 99
Projected dimension	64

All the models are implemented using TensorFlow 2.6.0 and trained on NVIDIA RTX 2070 Mobile. We pre-trained all the models using the ADAM optimization algorithm [45] with a maximum of 50 gradient updates. We update the weights with a learning rate of 0.001 and use a mini-batch size of 100. Both Midformer and Transformer incorporate 2 to 4 attention layers. The projected dimension of Midformer is $d = 64$, and the number of heads is $H = 8$. The number of patches is fixed at $k = 3, 9, 11, 99$. Table III describes the detailed information of the hyper-parameters.

We fine-tune the pre-trained model using the stochastic gradient descent (SGD) method with a momentum of 0.9 and a learning rate of 0.01.

C. Performance Metrics

We use two metrics to evaluate the performance of the proposed Transformer model, which are the mean absolute error (MAE) and the signal aggregate error (SAE). These two metrics are defined as follows.

$$\text{MAE} = \frac{1}{T}\sum_{t=1}^{T}|\hat{y}_j(t) - y_j(t)| \tag{4}$$

$$\text{SAE} = \frac{1}{r_j}\left|\hat{r}_j - r_j\right|, \tag{5}$$

where T is the duration of the period used to predict the output; $y_j(t)$ is the ground truth of power consumption of appliance j and $\hat{y}_j$ is the predicted value by the NILM models; $\hat{r}_j$ and r_j are the predicted total energy consumption and the ground truth of appliance j over the period T, respectively.

D. Experimental Results and Discussions

Three scenarios are designed and examined in our experimental study, which are:

(i) The pre-trained model is evaluated on the same appliance in the same dataset;
(ii) The model is applied to a different dataset but on the same appliance;
(iii) The model learned using one appliance in one dataset is evaluated on other appliances in a different dataset.

Multiple cases are examined, which belong to these three scenarios and use the data from the two public datasets.

TABLE IV: Model Performances on the REFIT Dataset

Kettle	**Testing House 9**		**Testing House 20**		**Average**	
Model	MAE	SAE	MAE	SAE	MAE	SAE
s2p	10.882	0.054	5.162	0.058	8.022	0.056
Bi-GRU	11.072	0.076	6.958	0.074	9.015	0.075
Transformer	7.874	**0.052**	**3.971**	0.056	5.923	0.054
Midformer	**6.313**	0.062	4.081	**0.041**	**5.197**	**0.052**
Dishwasher	**Testing House 9**		**Testing House 16**		**Average**	
Model	MAE	SAE	MAE	SAE	MAE	SAE
s2p	14.683	0.463	14.622	0.292	14.653	0.378
Bi-GRU	15.408	0.294	24.665	1.290	20.037	0.792
Transformer	14.159	0.463	21.533	1.348	17.846	0.906
Midformer	**12.973**	**0.154**	**10.991**	**0.289**	**11.982**	**0.222**
Fridge	**Testing House 9**		**Testing House 15**		**Average**	
Model	MAE	SAE	MAE	SAE	MAE	SAE
s2p	25.145	0.240	25.465	**0.095**	25.305	**0.168**
Bi-GRU	**23.672**	**0.107**	27.150	0.230	25.411	0.169
Transformer	29.153	0.366	**23.970**	0.507	26.562	0.437
Midformer	23.853	0.261	24.900	0.418	**24.377**	0.340
Washing Machine	**Testing House 15**		**Testing House 17**		**Average**	
Model	MAE	SAE	MAE	SAE	MAE	SAE
s2p	10.808	0.562	8.277	0.284	9.543	0.423
Bi-GRU	11.377	0.499	12.068	0.293	11.723	0.396
Transformer	10.573	0.562	10.373	0.244	10.473	0.403
Midformer	**9.236**	**0.281**	**6.694**	**0.229**	**7.965**	**0.255**
Microwave	**Testing House 17**		**Testing House 19**		**Average**	
Model	MAE	SAE	MAE	SAE	MAE	SAE
s2p	5.342	0.210	**3.984**	0.458	4.663	0.334
Bi-GRU	4.879	0.563	5.455	0.662	5.167	0.613
Transformer	6.505	0.594	4.507	0.266	5.506	0.430
Midformer	**4.395**	**0.190**	4.058	**0.250**	**4.227**	**0.220**

1) The REFIT Dataset: The results in terms of the evaluation metrics on the REFIT dataset are represented in Table IV, which covers Scenario (i) described above. In this experiment, models for each appliance is pre-trained using the REFIT training set. Next, the data for the same appliance from two unseen houses are used to evaluate the pre-trained model. For example, for kettle, the labeled kettle data from Houses 5, 7, and 13 are used to pre-train the models, and then the kettle data from Houses 9 and 20 are used to test the pre-trained models, while all the houses belong to the same REFIT dataset. Table IV shows that the proposed Midformer model achieves both lower MAE and SAE in most cases (i.e., 6 cases out of 10 for MAE and 7 cases out of 10 for SAE). The average MAE and SAE values are averaged over the two houses. Our model achieved the best MAE results in all the cases, as well as the best SAE results for all the cases except for fridge. Compared to the baseline model s2p [12], the MAE reductions for kettle, dishwasher, washing machine, microwave, and fridge are 35.21%, 18.23%, 16.54%, 9.35%, and 3.80%, respectively.

Fig. 4 presents the execution times of different models for training per epoch under different window sizes. The Transformer and Midformer models both have two attention layers. The training set includes 100K samples. From the figure, we can see that the s2p model [12] uses the least amount of time; our proposed model uses the second least amount of time. The traditional Transformer model, which has the same number of layers as Midformer, consumes the longest time for training. The Bi-GRU model [30] uses less training time than Transformer for most of the window sizes (except for $W = 100$K). However, it is still more time-consuming thank both s2p and Midformer. Considering the time and accuracy factors together, our proposed Midformer model consumes very little time for training and achieves the highest accuracy.

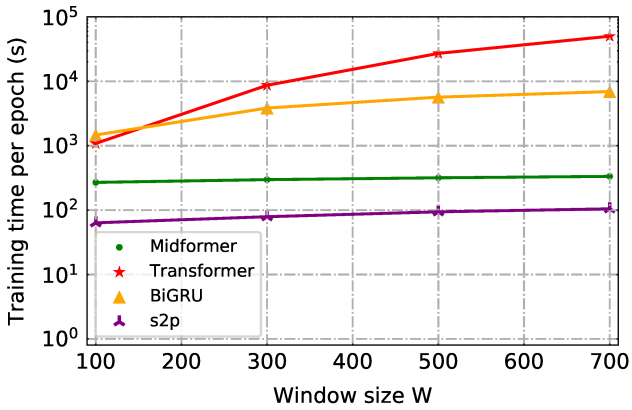


Fig. 4: Execution times of s2p [12], Bi-GRU [30], Transformer (full attention) [6], and Midformer on the training set.

Next, we conduct an ablation study to further investigate the effectiveness of the proposed model. For brevity, we only present the results using the first week of the testing set. The window size and the number of patches are important parameters in our model structure. Fig. 5 presents a comparison of the MAEs obtained by Midformer models with different window sizes for the kettle in House 9 and the washing machine in House 15. The figure shows that the best window size for each appliance is different, which is 99 for kettle and 693 for washing machine. An overly large window size might hurt the disaggregation performance and increase the model's training time. Choosing a proper window size is vital for saving the training cost. Note that the unique windows size for different appliances limits the transferability of a trained model to different appliances. Therefore, during the fine-tuning process in the following part of the experiments, we adopt the same window size of the pre-trained model for the fine-tuned model. We will explore the problem of transfer learning with different window sized models in our future work. Fig. 6 illustrates the effect of the number of patches on the model performance. We use washing machine as the subject of this study and the window size is set to 693. The figure shows that the best number of patches for washing machine is 11. We further test the washing machine model with different window sizes and different patch numbers. Table V shows the best number of patches and the best patch size for each given window size (i.e., 99, 297, and 693), as well as the best MAE result. We find that a larger window size requires a larger patch size accordingly to achieve the best performance.

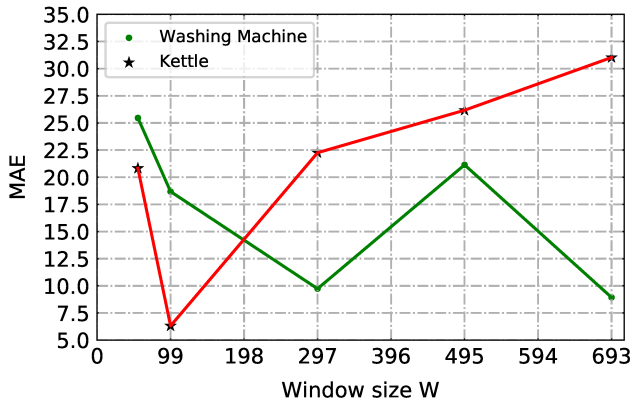


Fig. 5: MAEs obtained by Midformer models with different window sizes by testing the kettle in House 9 and the washing machine in House 15. The number of patches is set to 11.

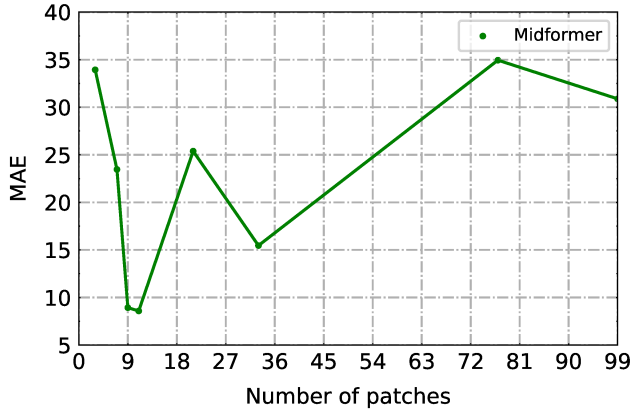


Fig. 6: MAEs achieved by Midformer models with different numbers of patches for washing machine, when the window size is set to 693.

TABLE V: The Best Number of Patches and the Best Patch Size Under Different Window Sizes (Washing Machine)

Window size	99	297	693
Best number of patches	33	9	11
Best patch size	3	33	63
Best result (MAE)	10.88	8.93	8.55

TABLE VI: Ablation Study: MAE Results

Washing Machine	Midformer	Midformer w/o Window Shifting
House 15	8.55	9.12

We next study the impact of window shifting on the Midformer performance. The results are given in Table VI, which is obtained for the washing machine in House 15 with a window size of 693 and a patch size of 63. We replace the cyclically shifted window with un-shifted Transformer blocks, and find the performance drops by 6.67%.

2) The UKDALE Dataset: In this experiment, we verify the transferability performance of the pre-trained model across different domains (i.e., different datasets and appliances). We first fine-tune the pre-trained model, which was originally learned using one appliance in the REFIT dataset, with a small portion of new data from the UKDALE dataset, and then use the test set of UKDALE to verify the performance of the model on the same or different appliance (see Table II). These experiments cover Scenarios (ii) and (iii) described above.

The performance of the pre-trained models on the unseen UKDALE dataset is presented in Tables VII and VIII. Table VII are the results of the pre-trained models without fine-tuning, while Table VIII are the results of the pre-trained models after fine-tuning, on the same appliance or an unseen appliance. The first column of the tables indicates the appliance and dataset learned by the pre-trained model. The second column indicates the unseen test dataset and corresponding appliances (same or different). The remaining columns are the MAEs and SAEs achieved by the four models.

From Table VII, we can see that the results of the pre-trained models without fine-tuning have relatively large errors. When the pre-trained model uses the same appliance as the test appliance, the test results are better than that using a different appliance. Except for the Bi-GRU [30] model, the other three models achieve similar MAE and SAE values, which are around 85 and 3, respectively.

From Table VIII, it is obvious that fine-tuning has been very effective in reducing the error of all the models on unseen dataset and appliances, since both the MAEs and SAEs of all the models are greatly improved. For example, the average MAE of Midformer is reduced from 84.566 to 7.121, and the average SAE is reduced from 2.586 to 0.056, after fine-tuning (huge improvements). In the table, the bold numbers in each row indicate the *best result* among the four models obtained for the test set when using a pre-trained model of a particular appliance. For example, for pre-trained model using kettle in REFIT and the target appliance kettle in UKDALE, the Midformer model achieves the smallest MAE of 4.183 and the smallest SAE of 0.041. The number marked by symbol "†" indicates the *best model* for that target appliance among all the pre-trained models. For example, for the target appliance kettle, the pre-trained model of Midformer learned from the source appliance dishwasher achieves the best MAE of 3.837. To better present the results, we have summarized such information in Table IX.

We can make the following observations from these results. (i) The proposed Midformer model outperforms all other models on average and in most specific cases. (ii) Our proposed model achieves superior transferability performance, which means we can use the pre-trained Midformer model using one appliance for all other target appliances, resulting greatly reduced cost for model pre-training. (iii) In most cases, the best result for a target appliance is obtained with the model pre-trained using the same appliance. The best pre-trained model for fridge, washing machine, and microwave in the UKDALE dataset is the model learned from the same appliance in the REFIT dataset, respectively. This is intuitive since the pre-trained model will perform well if the test data and training data share similar features. In Table IX, the proposed Midformer model accounts for four of the five best results of transfer learning.

The predicted power consumption values of House 2 in the

TABLE VII: Results of the Pre-trained Model without Fine-tuning Tested on the UKDALE Dataset

Pre-trained Dataset	Testing Dataset	**Bi-GRU**		**s2p**		**Transformer**		**Midformer**	
REFIT	*UKDALE*	MAE	SAE	MAE	SAE	MAE	SAE	MAE	SAE
Kettle	Kettle	16.579	**0.163**	22.642	0.442	16.204	0.268	**15.099**	0.234
	Dishwasher	72.909	**0.498**	**66.627**	0.669	70.220	0.562	71.449	0.558
	Fridge	47.079	**0.783**	**44.102**	0.786	46.458	0.798	46.625	0.795
	Washing machine	26.613	0.331	**21.459**	**0.122**	25.377	0.242	25.929	0.259
	Microwave	24.651	1.432	**18.755**	**0.625**	23.448	1.272	23.580	1.297
Dishwasher	Kettle	81.610	0.325	60.178	0.372	44.579	0.766	**15.099**	**0.234**
	Dishwasher	80.330	**0.103**	81.828	0.329	**47.492**	0.798	71.449	0.558
	Fridge	40.446	0.954	**39.396**	0.995	40.993	**0.946**	46.625	0.795
	Washing machine	44.862	0.601	**41.812**	0.939	44.541	0.632	45.929	**0.259**
	Microwave	44.487	0.294	44.362	0.362	**42.864**	**0.263**	43.580	1.297
Fridge	Kettle	371.049	8.047	318.502	6.556	306.362	6.264	**303.152**	**6.127**
	Dishwasher	379.803	**3.338**	**305.632**	4.484	308.999	4.471	313.630	4.569
	Fridge	25.034	0.321	25.621	0.873	**24.273**	**0.218**	25.702	0.222
	Washing machine	157.459	12.417	109.502	8.172	**107.688**	**8.087**	110.956	8.388
	Microwave	1224.569	28.545	169.378	20.964	**168.284**	**20.870**	172.590	21.404
Washing machine	Kettle	197.971	3.073	**181.299**	**3.060**	216.437	4.070	183.575	3.073
	Dishwasher	171.177	2.266	162.226	**1.938**	149.851	2.800	**135.068**	1.949
	Fridge	47.722	0.752	**45.399**	0.800	68.355	0.766	50.924	**0.647**
	Washing machine	31.097	1.337	**19.867**	**0.432**	58.687	3.966	33.079	1.359
	Microwave	79.898	8.825	66.123	**7.040**	99.997	11.766	**65.980**	7.091
Microwave	Kettle	113.396	1.038	119.416	1.233	**56.051**	**0.424**	116.196	1.096
	Dishwasher	121.416	**0.515**	129.421	0.670	**62.974**	0.624	129.026	0.627
	Fridge	39.345	1.000	41.747	**0.919**	**39.344**	1.000	41.670	0.929
	Washing machine	**11.629**	0.995	17.279	**0.471**	11.726	0.985	16.329	0.545
	Microwave	9.974	0.657	**6.429**	**0.167**	9.271	0.718	7.698	0.202
average		98.444	3.144	86.360	2.537	83.619	2.943	84.566	2.586

TABLE VIII: Results of Pre-trained Model with Fine-tuning Tested on the UKDALE Dataset

Pre-trained Dataset	Testing Dataset	**Bi-GRU**		**s2p**		**Transformer**		**Midformer**	
REFIT	*UKDALE*	MAE	SAE	MAE	SAE	MAE	SAE	MAE	SAE
Kettle	Kettle	10.064	0.116	9.854	0.106	10.585	0.318	**4.183**	**0.041**
	Dishwasher	39.001	0.409	**4.463**	**0.017**	14.511	0.153	5.135	0.040
	Fridge	34.475	0.025	24.296	**0.015**	36.476	0.139	**17.081**	0.061
	Washing machine	9.540	0.715	12.604	0.194	19.102	**0.126**	**6.979**	0.185
	Microwave	14.192	1.014	5.800	0.169	4.275	0.018	**4.183**	**0.013**
Dishwasher	Kettle	55.162	0.241	4.471	0.017	6.874	0.058	†**3.837**	**0.010**
	Dishwasher	29.180	0.389	**4.820**	**0.009**	7.970	0.086	6.974	0.012
	Fridge	34.949	0.030	28.004	0.196	36.237	0.113	**15.312**	**0.162**
	Washing machine	10.137	0.758	11.812	0.328	9.490	0.328	**5.301**	**0.049**
	Microwave	18.649	0.516	3.762	0.187	5.414	0.128	**3.177**	**0.065**
Fridge	Kettle	64.616	0.440	8.009	0.023	5.159	**0.018**	**4.520**	0.043
	Dishwasher	36.583	0.173	5.639	0.031	6.094	0.014	**5.251**	**0.006**
	Fridge	24.059	0.032	13.798	0.083	16.588	0.144	†**13.132**	**0.050**
	Washing machine	13.342	0.503	8.553	0.523	7.008	0.277	**5.110**	**0.045**
	Microwave	13.889	0.455	5.402	0.250	5.497	0.175	**3.126**	**0.171**
Washing machine	Kettle	37.098	0.435	5.994	0.027	7.482	0.014	**5.213**	**0.003**
	Dishwasher	30.852	0.266	†**4.254**	0.012	5.377	**0.003**	5.406	0.040
	Fridge	35.310	0.110	24.393	0.285	34.425	0.322	**14.992**	**0.032**
	Washing machine	15.987	0.177	8.089	0.390	9.523	**0.055**	†**4.887**	0.114
	Microwave	23.553	1.177	4.267	0.020	7.303	0.053	**3.165**	**0.041**
Microwave	Kettle	8.424	0.078	8.268	0.068	7.443	0.064	**6.114**	**0.020**
	Dishwasher	6.406	0.082	6.389	0.065	6.014	**0.029**	**4.310**	0.039
	Fridge	27.256	0.120	17.572	**0.012**	**17.428**	0.036	22.551	0.022
	Washing machine	14.767	0.661	13.904	0.380	6.806	0.374	**5.456**	**0.059**
	Microwave	5.456	0.126	5.289	0.090	4.541	0.039	†**2.630**	**0.028**
Average		24.518	0.358	10.088	0.136	12.145	0.123	**7.121**	**0.056**

TABLE IX: Best Pre-trained Model for the UKDALE Test Set

Test appliance in UKDALE	**Pre-trained appliance** in REFIT	**Model**	**MAE**	**SAE**
Kettle	Dishwasher	Midformer	3.837	0.010
Dishwasher	Washing machine	s2p	4.254	0.012
Fridge	Fridge	Midformer	13.132	0.050
Washing machine	Washing machine	Midformer	4.887	0.114
Microwave	Microwave	Midformer	2.630	0.028

UKDALE dataset for the five appliances obtained by the four pre-trained models on the REFIT dataset (i.e., s2p, Bi-GRU, Transformer, and Midformer) for a specific time period are plotted in Fig. 7, along with the corresponding ground truth values. Note that the "Aggregate" values are the input to these models to be disaggregated into individual appliance's power consumption. The figure shows that the proposed Midformer model achieves the best performance compared to the three baseline models, except for dishwasher (which is consistent with the results in Table IX). The Bi-GRU model fails to predict the washing machine's power state at some time instances, i.e., the washing machine's state is on, but it is predicted as off (see Fig. 7(d)).

VI. Conclusions

In this paper, we proposed the Midformer model to tackle the NILM problem. We utilized patch-wise attention and reduced the query size to reduce the quadratic time complexity in traditional Transformer models to linear complexity. We also focused on the transferability performance of the models, which helped to reduce the model training cost and eased the deployment of the model in various environments. Our experimental study using two real-world datasets demonstrated the superior performance and stronger transferability of the proposed Midformer model over three baseline, state-of-the-art models on addressing the NILM problem.

References

[1] W. Li, T. Logenthiran, V.-T. Phan, and W. L. Woo, "Implemented IoT-based self-learning home management system (SHMS) for Singapore," *IEEE Internet of Things J.*, vol. 5, no. 3, pp. 2212–2219, June 2018.

[2] L. Wang, S. Mao, B. Wilamowski, and R. Nelms, "Pre-trained models for non-intrusive appliance load monitoring," *IEEE Trans. Green Commun. Netw.*, to appear. DOI: 10.1109/TGCN.2021.3087702.

[3] H. Zou, S. Mao, Y. Wang, F. Zhang, X. Chen, and L. Cheng, "A survey of energy management in interconnected multi-microgrids," *IEEE Access J.*, vol. 7, no. 1, pp. 72 158–72 169, June 2019.

[4] Y. Wang, Y. Shen, S. Mao, X. Chen, and H. Zou, "LASSO & LSTM integrated temporal model for short-term solar intensity forecasting," *IEEE Internet of Things J.*, vol. 6, no. 2, pp. 2933–2944, Apr. 2019.

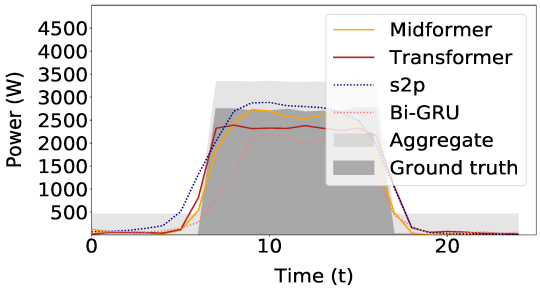
[5] A. Ruano, A. Hernandez, J. Ureña, M. Ruano, and J. Garcia, "NILM techniques for intelligent home energy management and ambient assisted living: A review," *MDPI Energies*, vol. 12, no. 11, p. 2203, June 2019.

[6] A. Vaswani, N. Shazeer, N. Parmar, J. Uszkoreit, L. Jones, A. N. Gomez, Ł. Kaiser, and I. Polosukhin, "Attention is all you need," in *Adv. Neural Inform. Process. Syst.*, Long Beach, CA, Dec. 2017, pp. 5998–6008.

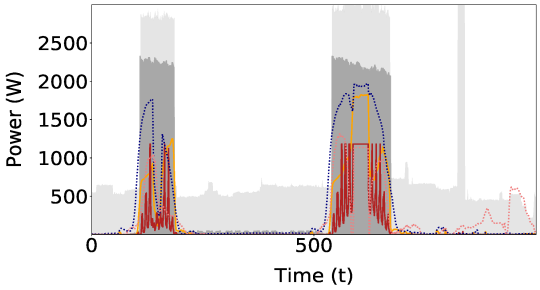
[7] A. Dosovitskiy *et al.*, "An image is worth 16x16 words: Transformers for image recognition at scale," *arXiv preprint arXiv:2010.11929*, June 2021. [Online]. Available: https://arxiv.org/abs/2010.11929

[8] S. Duan, W. Yang, X. Wang, S. Mao, and Y. Zhang, "Temperature forecasting for stored grain: A deep spatio-temporal attention approach," *IEEE Internet of Things J.*, vol. 8, no. 23, pp. 17 147–17 160, Dec. 2021.

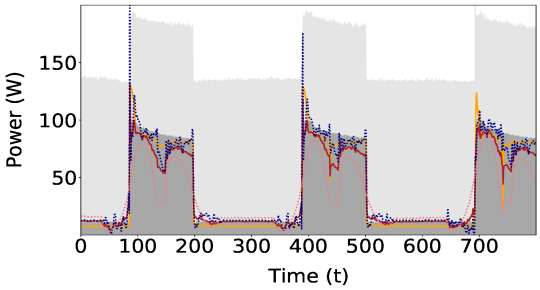
[9] Z. Yue, C. R. Witzig, D. Jorde, and H.-A. Jacobsen, "BERT4NILM: A bidirectional transformer model for non-intrusive load monitoring," in *Proc. 5th International Workshop on Non-Intrusive Load Monitoring*, New York, NY, Nov. 2020, pp. 89–93.



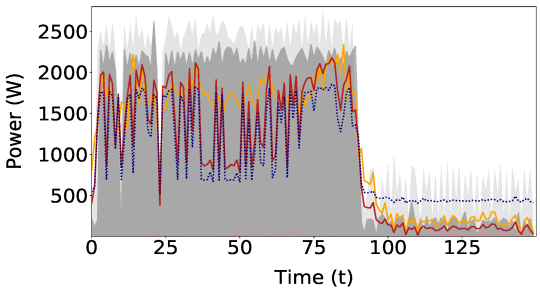
(a) Kettle.



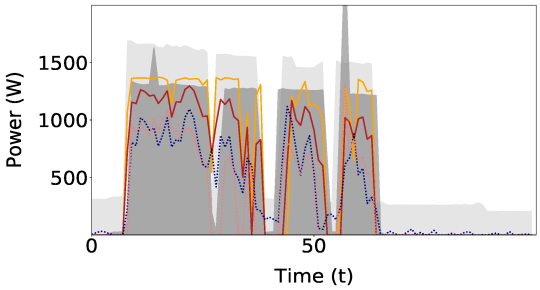
(b) Dishwasher.



(c) Fridge.



(d) Washing machine.



(e) Microwave.

Fig. 7: Comparison of predicted power consumption values by Midformer, Transformer, s2p, and Bi-GRU for the five appliances, along with the ground truth values.

[10] N. Lin, B. Zhou, G. Yang, and S. Ma, "Multi-head attention networks for nonintrusive load monitoring," in *Proc. 2020 IEEE Int. Conf. Signal Process., Commun. Comput.*, Macau, China, Aug. 2020, pp. 1–5.

[11] C. Wu, F. Wu, T. Qi, and Y. Huang, "Fastformer: Additive attention can be all you need," *arXiv preprint arXiv:2108.09084*, Sept. 2021. [Online]. Available: https://arxiv.org/abs/2108.09084

[12] M. D'Incecco, S. Squartini, and M. Zhong, "Transfer learning for non-intrusive load monitoring," *IEEE Trans. Smart Grid*, vol. 11, no. 2, pp. 1419–1429, Aug. 2019.

[13] S. M. Tabatabaei, S. Dick, and W. Xu, "Toward non-intrusive load monitoring via multi-label classification," *IEEE Trans. Smart Grid*, vol. 8, no. 1, pp. 26–40, June 2016.

[14] P. Huber, A. Calatroni, A. Rumsch, and A. Paice, "Review on deep neural networks applied to low-frequency NILM," *MDPI Energies*, vol. 14, no. 9, p. 2390, Apr. 2021.

[15] J. Z. Kolter and T. Jaakkola, "Approximate inference in additive factorial hmms with application to energy disaggregation," in *Proc. 2012 Int. Conf. Artif. Intell. Stat.*, La Palma, Canary Islands, Apr. 2012, pp. 1472–1482.

[16] M. Zhong, N. Goddard, and C. Sutton, "Signal aggregate constraints in additive factorial HMMs, with application to energy disaggregation," in *Adv. Neural Inform. Process. Sys.*, Montreal, CA, Dec. 2014, pp. 3590–3598.

[17] O. Parson, S. Ghosh, M. Weal, and A. Rogers, "Non-intrusive load monitoring using prior models of general appliance types," in *Proc. AAAI'12*, Toronto, CA, July 2012, pp. 356–362.

[18] H. Kim, M. Marwah, M. Arlitt, G. Lyon, and J. Han, "Unsupervised disaggregation of low frequency power measurements," in *Proc. 2011 SIAM Int. Conf. Data Mining*, Mesa, USA, Apr. 2011, pp. 747–758.

[19] B. Zhao, L. Stankovic, and V. Stankovic, "On a training-less solution for non-intrusive appliance load monitoring using graph signal processing," *IEEE Access J.*, vol. 4, pp. 1784–1799, Apr. 2016.

[20] K. He, L. Stankovic, J. Liao, and V. Stankovic, "Non-intrusive load disaggregation using graph signal processing," *IEEE Trans. Smart Grid*, vol. 9, no. 3, pp. 1739–1747, Aug. 2016.

[21] G.-Y. Lin, S.-C. Lee, J. Y.-J. Hsu, and W.-R. Jih, "Applying power meters for appliance recognition on the electric panel," in *Proc. 2010 IEEE Conf. Ind. Electro. Appl.*, Taichung, Taiwan, June 2010, pp. 2254–2259.

[22] J. Liao, G. Elafoudi, L. Stankovic, and V. Stankovic, "Non-intrusive appliance load monitoring using low-resolution smart meter data," in *Proc. 2011 IEEE Int. Conf. Smart Grid Commun.*, Venice, Italy, Nov. 2011, pp. 31–40.

[23] M. B. Figueiredo, A. De Almeida, and B. Ribeiro, "An experimental study on electrical signature identification of non-intrusive load monitoring (NILM) systems," in *Proc. 2011 Int. Conf. Adapt. Natural Comput. Alg.*, Ljubljana, Slovenia, Apr. 2011, pp. 31–40.

[24] C. Zhang, M. Zhong, Z. Wang, N. Goddard, and C. Sutton, "Sequence-to-point learning with neural networks for non-intrusive load monitoring," in *Proc. AAAI'18*, New Orleans, LA, Feb. 2018, pp. 1–8.

[25] C. Shin, S. Joo, J. Yim, H. Lee, T. Moon, and W. Rhee, "Subtask gated networks for non-intrusive load monitoring," in *Proc. AAAI'19*, vol. 33, Honolulu, HI, Jan. 2019, pp. 1150–1157.

[26] K. Chen, Q. Wang, Z. He, K. Chen, J. Hu, and J. He, "Convolutional sequence to sequence non-intrusive load monitoring," *J. Engineering*, vol. 2018, no. 17, pp. 1860–1864, Nov. 2018.

[27] K. Chen, Y. Zhang, Q. Wang, J. Hu, H. Fan, and J. He, "Scale-and context-aware convolutional non-intrusive load monitoring," *IEEE Trans. Power Syst.*, vol. 35, no. 3, pp. 2362–2373, Nov. 2019.

[28] L. Mauch and B. Yang, "A new approach for supervised power disaggregation by using a deep recurrent LSTM network," in *Proc. IEEE GlobalSIP'15*, Orlando, FL, Dec. 2015, pp. 63–67.

[29] J. Kim, T.-T.-H. Le, and H. Kim, "Nonintrusive load monitoring based on advanced deep learning and novel signature," *Hindawi Computational Intelligence Neuroscience*, vol. 2017, Article ID 4216281, Oct. 2017.

[30] O. Krystalakos, C. Nalmpantis, and D. Vrakas, "Sliding window approach for online energy disaggregation using artificial neural networks," in *Proc. 10th Hellenic Conf. Artificial Intell.*, Patras, Greece, July 2018, pp. 1–6.

[31] M. Kaselimi, N. Doulamis, A. Voulodimos, E. Protopapadakis, and A. Doulamis, "Context aware energy disaggregation using adaptive bidirectional LSTM models," *IEEE Trans. Smart Grid*, vol. 11, no. 4, pp. 3054–3067, July 2020.

[32] J. Kelly and W. Knottenbelt, "Neural NILM: Deep neural networks applied to energy disaggregation," in *Proc. 2nd ACM Int. Conf. Embedded Syst. for Energy-Efficient Built Environments*, Seoul, South Korea, Nov. 2015, pp. 55–64.

[33] R. Bonfigli, A. Felicetti, E. Principi, M. Fagiani, S. Squartini, and F. Piazza, "Denoising autoencoders for non-intrusive load monitoring: improvements and comparative evaluation," *Elsevier Energy and Buildings*, vol. 158, pp. 1461–1474, Jan. 2018.

[34] D. Murray, L. Stankovic, V. Stankovic, S. Lulic, and S. Sladojevic, "Transferability of neural network approaches for low-rate energy disaggregation," in *Proc. IEEE ICASSP'19*, Brighton, UK, May 2019, pp. 8330–8334.

[35] A. M. Ahmed, Y. Zhang, and F. Eliassen, "Generative adversarial networks and transfer learning for non-intrusive load monitoring in smart grids," in *Proc. IEEE SmartGridComm'20*, Tempe, AZ, Nov. 2020, pp. 1–7.

[36] Y. Liu, L. Zhong, J. Qiu, J. Lu, and W. Wang, "Unsupervised domain adaptation for non-intrusive load monitoring via adversarial and joint adaptation network," *IEEE Trans. Ind. Inform.*, vol. 18, no. 1, pp. 266–277, Jan. 2022.

[37] I. J. Goodfellow, "On distinguishability criteria for estimating generative models," *arXiv preprint arXiv:1412.6515*, May 2015. [Online]. Available: https://arxiv.org/abs/1412.6515

[38] T. Salimans, I. Goodfellow, W. Zaremba, V. Cheung, A. Radford, and X. Chen, "Improved techniques for training GANs," *Advances in Neural Information Processing Systems*, vol. 29, pp. 2234–2242, Dec. 2016.

[39] S. Wang, B. Z. Li, M. Khabsa, H. Fang, and H. Ma, "Linformer: Self-attention with linear complexity," *arXiv preprint arXiv:2006.04768*, June 2020. [Online]. Available: https://arxiv.org/abs/2006.04768

[40] D. Bahdanau, K. Cho, and Y. Bengio, "Neural machine translation by jointly learning to align and translate," *arXiv preprint arXiv:1409.0473*, May 2016. [Online]. Available: https://arxiv.org/abs/1409.0473

[41] Z. Liu, Y. Lin, Y. Cao, H. Hu, Y. Wei, Z. Zhang, S. Lin, and B. Guo, "Swin transformer: Hierarchical vision transformer using shifted windows," *arXiv preprint arXiv:2103.14030*, Aug. 2021. [Online]. Available: https://arxiv.org/abs/2103.14030

[42] T. Lin, Y. Wang, X. Liu, and X. Qiu, "A survey of transformers," *arXiv preprint arXiv:2106.04554*, June 2021. [Online]. Available: https://arxiv.org/abs/2106.04554

[43] D. Murray, L. Stankovic, and V. Stankovic, "An electrical load measurements dataset of United Kingdom households from a two-year longitudinal study," *Scientific Data*, vol. 4, no. 1, pp. 1–12, Jan. 2017.

[44] J. Kelly and W. Knottenbelt, "The UK-DALE dataset, domestic appliance-level electricity demand and whole-house demand from five UK homes," *Scientific Data*, vol. 2, no. 1, pp. 1–14, Mar. 2015.

[45] D. P. Kingma and J. Ba, "ADAM: A method for stochastic optimization," *arXiv preprint, arXiv:1412.6980*, Jan. 2017, [online] Available: https://arxiv.org/abs/1412.6980.