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Active and Reactive Power Sequences for Energy Disaggregation with Deep Learning Models

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***Abstract*—Non-Intrusive Load Monitoring (NILM) aims to decompose the aggregated power signal of a household smart meter into the power consumption of individual appliances. This information about consumption can potentially lead to energy savings by changing consumer behavior or facilitating the development of flexibility at the residential level. Deep learning methods have been shown to be the most successful in solving this problem. Nevertheless, these methods focus, most of the time, only on the measurement of the active power neglecting other available information such as reactive power. This paper evaluates the impact of adding reactive power sequences in such methods. In particular, we evaluate the impact of reactive power sequences in two state-of-the-art methods: one updated sequence-to-point Convolutional Neural Network (CNN) that we designed and one Variational Autoencoder (VAE) from the literature. Our experiments show that the addition of reactive power improves the performance of both algorithms on the UK-DALE dataset.**

***Index Terms*—Energy disaggregation, non-intrusive load monitoring, deep learning, reactive power, sequence-to-point.**

I. Introduction

Non-Intrusive Load Monitoring (NILM), also known as Energy Disaggregation (ED) is a method to estimate the energy consumption of individual appliances within a building using a single-point measurement, the smart/digital meter. It is termed non-intrusive because it only requires one measurement of the aggregated consumption at the basis of the building. In contrast, Intrusive Load Monitoring (ILM) requires a measurement device for each load to be monitored, which can be expensive, inconvenient, and laborious to maintain.

Today, the electric power system must be adapted to integrate an increasing proportion of renewable energy sources into the energy mix and to handle the evolution of electricity consumption. Changes at the residential level are mandatory for the optimization of the power system as residential consumption represents an important portion of electrical energy consumption. In this context, the deployment of a successful NILM algorithm could offer many benefits. NILM can provide residential consumers with detailed insights into their energy consumption and the specific contribution of each appliance. This consumption feedback can positively influence consumer behavior leading to a reduction in their overall consumption and their electricity bills. According to [1], overall energy feedback can lead to a consumption reduction between 5% and 20%. Disaggregated feedback could lead to a higher reduction. However, to our knowledge, this superior impact is yet to be proven, as discussed in [2] and [3]. Additionally, ED could facilitate the development of residential flexibility by estimating demand response potential through providing information about the proportion of flexible loads and by analyzing the impact of consumption reduction incentives.

In this paper, we propose to improve state-of-the-art Deep Learning (DL) disaggregation methods such as a Sequence-to-Point (S2P) Convolutional Neural Networks (CNN) and a Variational Autoencoder (VAE) by incorporating reactive power. Unlike state-of-the-art DL models, our proposed models use two-dimensional time series composed of both active and reactive power as input. This leads to a reduction in Mean Absolute Error (MAE) by 30% and 11%, and in Signal Aggregated Error (SAE) by 57% and 36%, respectively. The remainder of the paper is structured as follows: Section II presents a literature review and highlights the relevance of our contribution. Sections III and IV present the algorithms and the experiments used to test our proposal. Finally, Sections V and VI present the results and conclusions of our work.

II. Related works and contributions

NILM was first introduced in 1992 by George W. Hart [4]; since then, a large number of publications have contributed to the subject, especially in the last decade, due to the large-scale deployment of smart meters, the increase in computer capabilities, and the increasing need for an energy transition. NILM methodologies are various, they can be classified between supervised and unsupervised methods according to the data needed for the development of the algorithm. For supervised methods, a labeled dataset is required to train the algorithm. In the context of ED, a labeled dataset is a dataset that contains measurements of the appliance consumption as well as the measurement of the aggregated consumption at the building level at the same time. On the other hand, unsupervised methods require only information about the appliance consumption. Supervised methods generally perform better, but labeled datasets are more costly and challenging to collect.

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NILM methods can also be classified according to their objective. Regression methods estimate the power consumption of the appliances at each time step, and classification methods estimate whether the appliance is running or not at each time step. Although these two objectives are strongly linked, they can lead to different algorithm implementations.

In the literature, popular disaggregation methods include methods based on Factorial Hidden Markov Models (FHMM), optimization methods, methods based on VI trajectory, or deep learning methods.

FHMM is a probabilistic model where each appliance is represented by a Markov process. It takes aggregated active power sequences as input and outputs the most likely appliance consumption state sequences. One of its main advantages in the NILM context is that the model's parameters can be learned in an unsupervised way. Multiple variations of the FHMM have been proposed in the literature. In [5], the authors proposed an inference method that exploits the additive structure of FHMM for ED. In [6], the authors proposed a Conditional Factorial Hidden Semi Markov Model (CFHSMM) that allows the use of additional features such as time of the day or weeks, and that considers the state duration of the appliances. In [5], a new approximate inference procedure is proposed to handle a large number of appliances. In [7], disaggregation performances of FHMM are improved using both the active and reactive power sequences. In [8], a Time-Efficient FHSMM is proposed to improve the computational efficiency of classical FHSMM. In [9], the authors used Adaptive Density Peak Clustering (ADPC) to find the initial parameters of the HMM models.

Energy disaggregation can be presented as an optimization problem, where the objective is to minimize the difference between the aggregated measured power and the sum of estimated power consumptions of individual appliances. The NILM algorithms based on optimization are also unsupervised. In [10], a multi-objective optimization method is presented; the two objectives are minimization of the active and reactive power differences. In [11], the authors proposed a multi-objectives NILM optimization method with five objective functions using active, reactive, and apparent power, currents, and harmonics. In [12], a NILM optimization method that uses the amplitude and phase of the fundamental current is proposed. In [13], temporal dependencies between the appliance are used as constraints, as well as the state duration of the appliance. In [14], the authors proposed a Constrained Multi-Objective Problem (CMOP). The two objectives are the sparsity and the disaggregation error.

In VI trajectory methods, a curve of the voltage versus current during the operation of an appliance is created from the aggregated signals. This plot is then used to classify the appliance. In [15], a Support Vector Machine (SVM) is used to classify the VI trajectories. In [16] and [17], color is added to the VI trajectory representation to include more information. In [18], a comparison of VI trajectory classification is done between CNN and Random Forest (RF).

Deep learning methods have been very popular these last few years as they tend to achieve higher disaggregation performance [19], [20] [21], [22]. DL techniques have the potential to extract the relevant information in the aggregated signals and adapt well to unseen houses. Their main disadvantage is the need for a labeled dataset. In particular, DL methods composed of CNN have been particularly successful. In [23], the authors proposed a S2P CNN architecture; the input is a sequence of aggregated power, and the output is the estimated power of one appliance at the midpoint of the sequence. In [22], the authors analyzed a Sequence-to-Sequence (S2S) denoising Autoencoder (dAE). In [24] and [25] two S2S VAEs based on convolutional layers were proposed. In [26], the authors proposed a S2P deep neural network based on residual connection and attention mechanism. In these DL models and the vast majority of publications, only aggregated sequences of the active power are used. To the best of the author's knowledge, active and reactive power sequences are only used in [27] to improve the performance of a dAE. ED is an ill-posed problem, and all the easily available information must be used to obtain methods with high performance. Today, modern smart meters like the Belgian smart meter do not only measure active power but also voltage, current, and apparent power. This information could be used to improve the performance of the existing algorithms.

This paper proposes the use of active and reactive power sequences for the estimation of appliance power consumption with deep-learning regression methods. It is supposed that the additional use of reactive power will improve not only the detection of the appliance in use but also the estimation of its power consumption. In particular, the impact of a two-dimensional (2D) input with active and reactive power is evaluated in two state-of-the-art methods, an updated version of the S2P algorithm introduced in [23] and a high-performing VAE from literature (VAE-NILM) [25].

III. Proposed method

Sequence-to-point learning for NILM was first introduced in [23]. The idea of S2P is to use sequences of aggregated power as input of a neural network to predict the appliance power at the mid-point of the sequence. S2P has been proved to be more efficient than S2S in [23]. In S2S, a single element of the disaggregated signal is predicted multiple times, and the inference is the mean of these predictions. This leads to lower performance as elements at the edge of the input window are poorly predicted. The mid-point prediction allows the algorithm to use past, present, and future aggregated consumption to predict the appliance power.

Compared to the original paper, we propose two improvements to the algorithm. First, active and reactive aggregated power sequences are used at the input instead of only the active power sequences. This changes the input from 1D to 2D. The concept of a sliding window for a 2D S2P prediction is illustrated in Fig. 1. The addition of reactive power should improve the detection of appliances in use and the estimation of their power consumption, thus improving the overall disaggregation results. Active (P) and reactive (Q)

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power are indeed strongly linked together and to the appliance impedance (Z) through the apparent power (S) in 1:

$$S = \sqrt{P^2 + Q^2} = V_{rms} I_{rms} = \frac{V_{rms}^2}{Z} \tag{1}$$

The use of reactive power can improve the signature of each appliance by making them more unique and containing more information. Second, the architecture of the original CNN is modified with the following elements: the addition of Batch Normalization (BN) layers, the addition of Max Pooling (MP) layers, and the addition of a Dropout (Dr) layer. This updated architecture is presented in Fig. 2.

The batch normalization layer, introduced in 2015 in [28], is a layer that normalizes its inputs during training. By maintaining stable input distributions across different layers, BN mitigates issues like vanishing or exploding gradients, accelerates convergence, enhances model performance, and reduces sensitivity to weight initialization. BN has been effectively applied to improve the performance of DL NILM models in [25], [29], [30], and [31].

Dropout is a popular regularization technique in deep neural networks introduced in 2012 in [32]. It helps prevent overfitting by randomly dropping a fixed percentage of nodes during training.

Max pooling is a technique used to reduce the dimension of the input feature map. A reduced number of parameters reduces the risk of overfitting and helps generalize the model to unseen data. It also lowers the computational cost of the model. With MP, the updated S2P has three million parameters instead of thirty million in the original architecture.

The model architecture and hyper-parameters are inspired by the literature and have been adapted either heuristically or by grid-search. An analysis of the optimal number of layers with a similar architecture is done in [30]. Like in [27] and [30], although the input has a two-dimensional shape (window size, 2), the model is composed of 1D convolutional layers, meaning that the kernels are only moving along the temporal axis. The input data are pre-processed before training and inference. The 2D input and the target are standardized by subtracting the mean and standard deviation of the appliance active power with the same values as in [23].

The S2S VAE is exactly the same as in the original paper [25], except for the input layer, which has been modified to accept 2D input sequences. The original *python* code is available in the VAE-NILM repository[1].

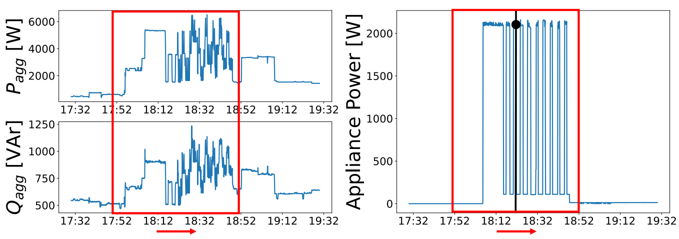

Fig. 1. Sliding window concept for a 2D S2P.

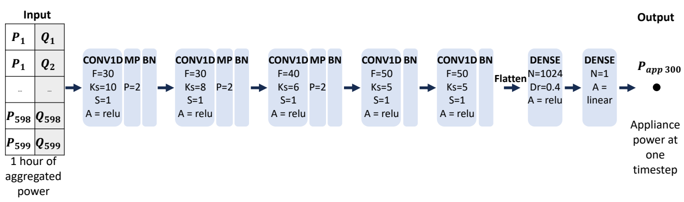

Fig. 2. Architecture of the proposed updated S2P algorithm. Activation (A), Dropout (Dr), Filter (F), Kernel size (Ks), Neurons (N), Stride (S).

IV. EXPERIMENTS

The UK-DALE dataset [33] was selected to conduct the experiments and compare our model with others. The UK-DALE dataset contains a recording of the whole house power and appliance power of five houses in the UK with a sampling frequency of 1/6 Hz. Only houses 1, 2, and 5 were used in our experiments as they are the only ones having a recording of the active (P) and apparent power (S). The reactive power (Q) is calculated with $Q = \sqrt{S^2 - P^2}$.

For the updated S2P, the length of the input sequences is one hour or 599 points. This length could be adapted for each appliance, like in [22]. Nevertheless, for simplicity's sake, the input sequence length is the same for each appliance. To create the training set, sequences are selected with a stride of 20 points (2 min). h1 and h5 are used for training, and h2 for testing. It is essential to evaluate the model on unseen houses as it will be the case for real-life applications. The experiments are done in *python* with *Tensorflow.keras*. The number of epochs is set to ten, *Adam* optimizer is used, and Ridge regularization strength is set to 10^{-7}.

The models are trained and tested ten times for each appliance, and the average results are presented. The models are evaluated with two popular metrics: the Mean Absolute Error (MAE) and the normalized Signal Aggregated Error (SAE). The MAE of appliance i is given by:

$$MAE^{(i)} = \frac{1}{T} \sum_{t=1}^{T} |y_t^{(i)} - \hat{y}_t^{(i)}| \tag{2}$$

Where $y_t^{(i)}$ and $\hat{y}_t^{(i)}$ are the ground truth active power and the inferred active power of appliance i. The SAE of the ith appliance is given by:

$$SAE^{(i)} = \frac{|E^{(i)} - \hat{E}^{(i)}|}{E^{(i)}} \tag{3}$$

Where $E^{(i)}$ and $\hat{E}^{(i)}$ are the ground truth energy consumption and the inferred energy consumption of appliance i.

V. RESULTS AND DISCUSSION

Fig. 4 presents examples of disaggregation with our 2D S2P. Table I presents a comparison of the results of our experiments. For our updated S2P algorithm, introducing the reactive power sequence improved the MAE and SAE on every appliance except for the MAE of the WM. On average, the MAE is improved by 30% and the SAE by 57%. For

[1]https://github.com/ETSSmartRes/VAE-NILM

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the VAE-NILM algorithm, the MAE and SAE are improved for most appliances. For the kettle, both the MAE and SAE are worse. On average, the MAE is improved by 11% and the SAE by 36%. It is worth noting that this comparison is fair regarding model complexity. The four models each have approximately 3.8 million parameters. Introducing the reactive power increases the number of parameters by a few hundred as it affects only the first convolutional layer of the models.

Table II compares the improved algorithms against the performance of state-of-the-art algorithms from the literature. While comparing the performance, it is important to note that our results are the average of ten simulations. However, we do not know if the results from the literature are also an average of multiple simulations. It is also interesting to note that the other papers use houses 1,3,4, and 5 for training, whereas we only use houses 1 and 5. Against state of the art, the 2D VAE-NILM and the 2D updated S2P are the best and the second best for the MAE metric. They are the second and the fourth best on the SAE metric. The SAE of the 2D updated S2P is significantly reduced because of his performance for the microwave. It can also be noted that our updated 2D S2P performs better than the original Seq2point algorithm, with an improvement of 35% for the MAE and 42% for the SAE.

Finally, Fig.3 presents a comparison of the microwave disaggregation with 1D or 2D input for the best model of our updated S2P. In this example, the addition of reactive power improved the detection as well as the estimation of the microwave power.

VI. Conclusions

This paper investigates the impact of incorporating reactive power sequences for energy disaggregation with DL models. We have demonstrated that the use of reactive power has a positive impact on the majority of the appliances for two state-of-the-art architectures: a S2P CNN and a VAE, reducing in average their MAE by 30% and 11% and their SAE by 57% and 36%. However, since the impact is not positive for every appliance, reactive power could be selectively used only for appliances where it is most beneficial.

We believe that future DL models should incorporate reactive power as an input, as it provides a straightforward way to enhance performance. Additionally, we recommend developing new datasets that include aggregated reactive power, feature more instances of houses, represent modern appliances, and align with current smart meter capabilities.

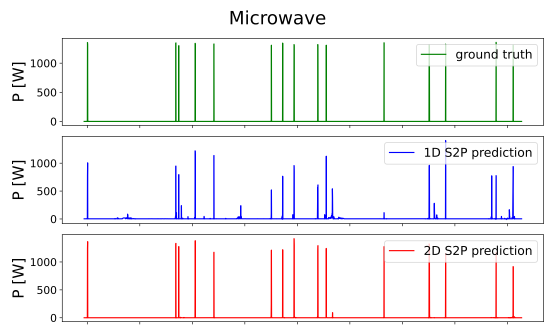

Fig. 3. Comparison of microwave disaggregation with 1D and 2D updated S2P.

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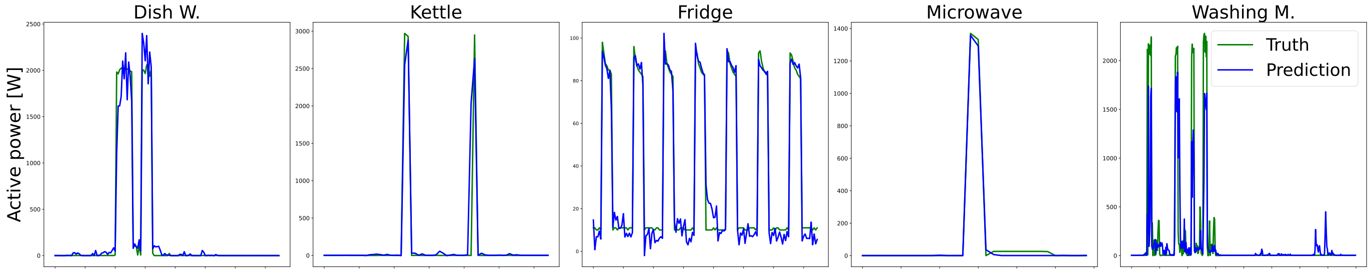

Fig. 4. Energy disaggregation with the updated S2P algorithm on the unseen house 2 of UKDALE dataset.

TABLE I
COMPARISON OF MODELS FROM EXPERIMENTS ON HOUSE 2 OF THE UK-DALE DATASET

Metric	Model	Kettle	Microwave	Fridge	Dish W.	Washing M.	Average
MAE [W]	1D VAE-NILM	**6.2 ± 0.4**	5.2 ± 0.2	14.9 ± 0.19	**10.7 ± 2.1**	6.3 ± 0.4	8.7
	2D VAE-NILM	6.6 ± 0.3	**2.0 ± 0.1**	**11.2 ± 0.3**	12.6 ± 1.8	**6.2 ± 0.6**	**7.7**
	1D updated S2P	9.0 ± 2.5	11.8 ± 2.9	12.2 ± 0.6	32.1 ± 3.8	**10.6 ± 2.5**	15.1
	2D updated S2P	**8.5 ± 1.6**	**4.2 ± 1.1**	**11.4 ± 0.7**	**17.2 ± 4.9**	11.5 ± 2.0	**10.6**
SAE	1D VAE-NILM	**0.17 ± 0.01**	0.42 ± 0.04	0.15 ± 0.02	0.13 ± 0.06	**0.37 ± 0.03**	0.25
	2D VAE-NILM	0.20 ± 0.01	**0.06 ± 0.02**	**0.11 ± 0.01**	**0.07 ± 0.07**	**0.37 ± 0.04**	**0.16**
	1D updated S2P	0.15 ± 0.07	1.10 ± 0.47	0.13 ± 0.03	0.61 ± 0.13	0.23 ± 0.12	0.44
	2D updated S2P	**0.09 ± 0.03**	**0.47 ± 0.19**	**0.10 ± 0.02**	**0.14 ± 0.08**	**0.16 ± 0.08**	**0.19**

TABLE II
COMPARISON OF MODELS FROM THE LITERATURE ON HOUSE 2 OF THE UK-DALE DATASET

Metric	Model	Kettle	Microwave	Fridge	Dish W.	Washing M.	Average
MAE [W]	AFHMM [23]	47.4	21.2	42.3	199.8	103.2	77.7
	Seq2point [23]	7.4	8.7	20.9	27.7	12.7	16.2
	CVAE [24]	7.0	7.5	18.1	19.6	10.8	13.0
	ResNet+att [26]	-	5.7	12.3	18.2	**6.2**	10.6
	2D VAE-NILM	**6.6**	**2.0**	**11.2**	**12.6**	**6.2**	**7.7**
	2D s2p	8.5	4.2	11.4	17.2	11.5	10.5
SAE	AFHMM [23]	1.06	1.04	0.98	4.5	8.28	1.89
	Seq2point [23]	0.07	0.49	0.12	0.64	0.28	0.33
	CVAE [24]	**0.06**	0.18	0.13	0.32	0.21	0.17
	ResNet+att [26]	-	0.17	**0.08**	0.21	**0.07**	**0.12**
	2D VAE-NILM	0.20	**0.06**	0.11	**0.07**	0.37	0.16
	2D updated S2P	0.09	0.47	0.10	0.14	0.16	0.19

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