Disaggregation of Community Level Energy Data to Individual Households

Using sequence-to-point learning

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Abstract

Non-intrusive load monitoring (NILM) is a well-researched concept that aims to provide insights into individual appliance energy usage without the need for dedicated meters. This paper explores the possibility of applying the NILM concept to disaggregate energy data from a community level to a household level. By doing so, it addresses privacy concerns associated with real-time household data collection through smart meters. The proposed approach leverages sequence-to-point learning, a deep learning method, to perform the disaggregation. A method that showed promising results in the domain of NILM. The results show good performance on the evaluation metrics, but they also show that the model does a poor job of capturing the load signature.

1 Introduction

Climate change is at a point where we need to make significant adaptations to stop it. Scientists state we are at a "code red" with 16 out of 35 measured vital planetary signs at record extremes in 2022 [16]. To limit the effects of climate change, people worldwide are creating policies. International treaties on climate change have been set in place, like the Paris Agreement [1] and the European Green Deal [2]. In all of these policies, the energy grid appears as one of the issues. The main issue with the power grid is that it is hard to scale up; meanwhile, the demand is increasing because of more extreme weather conditions and the transition from fossil fuels [14]. Take the switch to electric vehicles (EVs), for example; all this additional need for power might cause blackouts to the network [18].

Researchers have proposed hardware and software improvements to prevent outages on the network. Software-based improvements have become very popular because it is an expensive and time-consuming task to replace and expand the existing power grid [8]. The software-based approaches aim to give more insight into energy usage patterns. An example is non-intrusive load monitoring (NILM) [13] [24]. NILM aims to give insight into appliances' energy usage without measuring it directly. To illustrate, this could be determining whether the dishwasher is running based on data collected by an electricity meter. The benefit of doing this non-intrusively is that it is cheaper since meters no longer have to be bought and installed for all devices, and it also has less of a privacy concern. The data can better inform and educate consumers about their usage. For example, it can suggest doing laundry at night at a cheaper rate instead of during the day. The data gathered this way can also be used for more accurate forecasting, resulting in improved load balancing and optimisation of energy storage.

Conceptually, NILM can be seen as nothing more than performing disaggregation on a high-level data collection to get more detailed information on lower-level data. This raises the question of whether this concept can be applied to different layers within the power grid and of what use this information could be. In this paper, the question is whether the same concept used in NILM can be applied to disaggregate from a community level to a household level instead of from a household level to an appliance level. The relevance of this research comes from a privacy perspective. To perform NILM, real-time household data is needed. Smart meters can be used to acquire that data, but some people object to smart meters because of privacy concerns. The goal of this research is to replace the need for smart meters.

By shifting the domain, other cases can be discovered where the concept can be applied. There are three different areas where the gathered data could also be relevant: Fraud detection, apartment buildings, and load balancing.

Firstly, the data can be used as a means of fraud detection by energy companies. In most countries, energy consumption is measured by some meter (either a smart or an analogue meter). This system is susceptible to fraud as the machinery could be tempered, or the passed-on data could be faked. This is not such a significant issue in most Western countries, but consider the situation in Pakistan, for example. In the fiscal year 2022 to 2023, over 4 billion euros got stolen by energy theft [20].

Another use case of the data can be found in apartment buildings or other buildings that use a shared meter for multiple households. Household consumption differences can be substantial when a shared meter is used. By disaggregating the consumption data from these communities to households, landlords can educate their tenants on their consumption. If the predictions are accurate, they could be used to differentiate prices.

Lastly, this disaggregation could be utilised for improved forecasting. On a household level, load forecasting is challenging due to the very volatile data it deals with [3]. On the contrary, for data on a community level, it is easier to forecast the usage. It might be possible to get better forecasting results on a household level by profiting from the high accuracy of load forecasting on a community level and disaggregating this result. That is not the focus of this paper, but it lays the foundation for possible future research.

Non-intrusive load monitoring is a well-researched topic. Hart first addressed the issue in 1992 [9]. He proposed performing NILM by estimating appliance-specific power consumption signatures in that paper. That is still the most used method for applying NILM. Research has focused on improving the estimation of these load signatures. In recent years machine learning and deep learning methods have become increasingly popular [3; 23].

All of these papers state that privacy is one reason for performing NILM. The same privacy argument can also be made for using smart meters. Non-intrusive load monitoring to estimate household consumption has yet to be discussed in the literature. The question of this research is whether it is possible to apply the concept of NILM to communities to get information about households.

In the field of NILM, sequence-to-point learning was proposed as a method [22]. Sequence-to-point learning outperforms other deep learning methods, like sequence-to-sequence learning [11]. Deep learning methods often require sliding windows because of the long data sequences they train on. Sequence-to-point learning solves this, as the output of a window is a single point of the target appliance. This paper leverages the same method of sequence-to-point learning to perform desegregation from communities to households. The algorithm will be compared to the ground truth and a baseline to evaluate the performance.

The rest of the paper is structured in the following way. Section 2 will explain the basic concepts behind NILM sequence-to-sequence learning. Then in Section 3, sequence-to-point learning will be explained as part of the methodology. Section 4 explains the experimental setup, giving more detailed information about the data, model, and evaluation. Section 5 contains the results. Then some ethical implications are discussed in section 6. Section 7 contains a discussion of the results. Lastly, section 8 contains some conclusions and ideas for future work.

2 Background

This section gives background information about non-intrusive load monitoring as it is a niche research branch, even though it applies well-known algorithms. After, sequence-to-sequence learning is explained as this knowledge is needed to understand why this research uses sequence-to-point learning.

2.1 NILM

Non-intrusive load monitoring as a concept is nothing new. In 1992, an extensive paper was published describing the advantages and disadvantages and the steps required for performing NILM [9]. The idea of NILM was already described in earlier papers that got less attention, as they all got less than ten citations. Hart proposed a method of NILM where the disaggregation happens by only looking at the power consumption of individual appliances. Let $P(t)$ be the total consumption at some time t, then the intuition behind Hart's idea follows from equation 1.

$$P(t) = p_1(t) + p_2(t) + ... + p_n(t) = \sum_{i=1}^{n} p_i(t) \qquad (1)$$

The algorithm should now perform a decomposition of $P(t)$ based on the knowledge of every $p_i(t)$ that indicates the consumption of that single appliance. This requires appliance models to be generated to estimate every single p_i. Hart divided them into three classes:

1. **ON/OFF**: A boolean model where the appliance can be either on or off. E.g. toasters, light bulbs, or water pumps.
2. **Finite State Machines (FSM)**: A model that has a finite set of consumption levels. E.g. dishwashers or laundry machines.
3. **Continuously Variable**: A model that can have an infinite amount of states. E.g. light dimmers or speed drills.

In research, these are the classes used for approximating appliance consumption signatures. Later on, a fourth class has been proposed [21]:

4. **Permanent Consumer**: A model mimicking appliances that are always on and consume a constant amount of energy. E.g. smoke detectors.

The classes above describe how to model a single appliance. That fits into a more general NILM framework that follows four stages [23]:

1. Data Acquisition and Pre-processing
2. Event Detection
3. Feature Extraction
4. Load Identification

Firstly, there is a data acquisition and pre-processing stage. For this, both low-frequency and high-frequency energy meters are used. To capture the electrical noise created by electric signals, high-frequency meters are required but are more expensive. In general, data acquisition tries to get consumption data on a household level. An alternative is to get data on a circuit level [12]. A benefit is that there are fewer devices to approximate, which increases the cost and installation complexity. The above is all data acquisition. After that, pre-processing is still needed due to missing data caused by network failure, for example.

Secondly, there is an event detection phase. The event detection phase identifies transition changes between appliances turning ON and OFF or vice versa [19].

Thirdly, there is a feature extraction phase. During feature extraction, the previously found events are modelled. Steady-state or transient-based features can either do this. Steady-state features try to model the appliance based on variations in their respective signature. An indicator is, for example, a switch from a high to a low value. Transient feature-based modelling tries to extract features like shape, size, duration, and harmonics of the transient waveforms. Transient-based feature extraction is better at segregating models when there are overlapping steady-state features but is more expensive in terms of costs. That is because at least 1000 samples per second are needed for transient-based feature extraction [21].

Lastly, there is a load detection phase. This is the phase during which the training happens. This is done both supervised [4] as well as unsupervised [6]. The challenge of supervised learning is that it needs adequately labelled data which is costly and takes a long time to collect. Unsupervised learning is also not the silver bullet, as it is generally less reliable and stable. Combinations of supervised and unsupervised learning have also been proposed [5]. All variations can provide valuable results, but all have their limitations.

2.2 Sequence-to-sequence

One proposed deep learning algorithm in NILM is sequence-to-sequence learning (seq2seq) [11]. Seq2seq was originally proposed to perform translation tasks from English to French [7]. The input, an English sentence, can be of variable length. Traditional deep neural networks generally cannot handle sequences that can not be encoded as fixed-length vectors and output variable-length vectors. Seq2seq solves this using two Long Short-Term Memory (LSTM) architectures [10]. First, a so-called decoder is used. That is an LSTM that takes the input sequence, one timestep at a time, to retrieve a fixed-size vector. This vector can then be used as an input to the second LSTM, called an encoder. The encoder returns the output sequence. Figure 1 shows what this architecture looked like for the translation task from English to French.

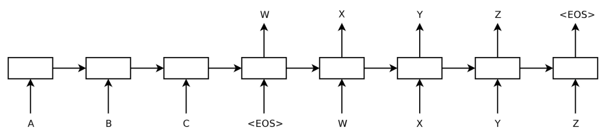

Figure 1: The model reads an input sentence “ABC” and produces “WXYZ” as the output sentence. The model stops making predictions after outputting the end-of-sentence token.

3 Methodology

This section outlines the data and method used to determine whether it is possible to disaggregate energy data from a community level to energy data on a household level. This work utilises sequence-to-point learning as a model to achieve that goal.

3.1 Dataset

Data collection is one of the challenges in NILM. It is an expensive and time-consuming task. Therefore energy consumption data collected by Pecan Street[1] is used for training and evaluating the model.

3.2 Sequence-to-point

NILM is a mapping from some input sequence to some output sequence. Disaggregating energy data from a community to a household level applies a similar mapping between sequences. The input and output sequences differ, but the concept is the same. For mapping between sequences of various lengths, seq2seq has proven useful. Generally, the models have to deal with large data sequences; to illustrate, six months of data with 15-minute intervals gives a vector of over 17,000 timesteps. Because of memory limitations and the problem of vanishing gradients sliding windows are often proposed as the solution. They have two issues in this case:

1. Each point in the output sequences gets predicted many times. As such, averages are often used to aggregate the results, but this smooths the edges. Usage patterns do generally not follow smooth patterns due to devices turning ON and OFF.
2. Some sliding windows make better predictions for certain output points. In particular, those windows where the element is near the midpoint will give better predictions. A simple sliding window algorithm can not exploit that information.

Sequence-to-point learning (seq2point) solves these problems by predicting the output point from the midpoint of every sliding window [22]. So for every sliding window, the corresponding midpoint of the output sliding window is predicted. By doing this, the prediction is made on the more relevant sliding window. Also, the model focuses on predicting the output points from the midpoint instead of the more difficult outputs on the edges. It does require padding the sequence with $\lceil W/2 \rceil$ zeros at the beginning and end, where W is the length of the sliding window. The need for averaging has also vanished, as each point is only predicted once.

[1] https://www.pecanstreet.org/dataport/

4 Experimental Setup

This section describes how the data was processed. After it describes how this data is used in the model, and what the model looks like. Finally an elaboration on the error measures follows.

4.1 Data

Data collected by Pecan Street was used for this research. They are a research institute gathering high-resolution energy data. They have collected household energy consumption data in 3 states: California, New York, and Texas. The data is available in 1-second, 1-minute, and 15-minute intervals. People connected to a university can get free access to data from 25 homes per state with at least six months' worth of data. The data contains various types of homes, like single-family homes and apartments. All houses' energy usage of appliances is measured, including energy provided by solar panels and energy given back to the grid.

Because of hardware limitations, the 15-minute data was chosen, even though high-frequency data is preferred to capture the harmonics of the transient waveforms. The New York dataset was the only set that contained 100% of the data, but it only had 6 months worth of data. Therefore, the Texas dataset was chosen at the cost of needing more prepocessing. The dataset has one year worth of data collected in 2018.

4.2 Data processing

Before using the data in the seq2point model, it needed to be processed. In figure 3 an overview of the steps is given.

As a first step, the data to be used was selected. The data was collected on an appliance level and contains a column for every available appliance per house. Some houses have appliances, like solar panels, that can generate energy and give back to the grid. Keeping that data means that the model should be able to capture more temporal features, like day and night, for example. As this paper aims to prove that disaggregating from communities to households is possible, I decided not to include this extra complexity.

In a second preprocessing step outliers were detected and removed. Outlier detection was done using the empirical rule [15]. That rule of thumb states that approximately 99.7% of data lies within three standard deviations from the mean. All data points outside of that range were removed.

After outlier detection missing feature detection was performed. If at any time datapoints were missing the first five were filled with the latest known value. If more than 5 values were missing the consumption was set to zero Watt.

As a third step, the data was aggregated to households and communities. Aggregating to households was done by summing all devices excluding battery1, grid, solar, and solar2. After, the aggregation to communities was made. A community was defined as five houses within the same city, as

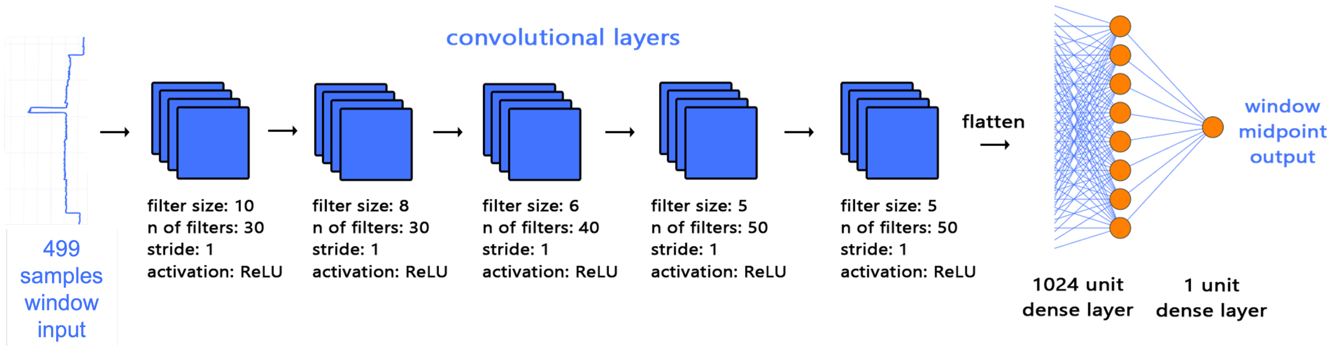

Figure 2: The model as used in this research is an adaption from the one used to research non-intrusive load monitoring.

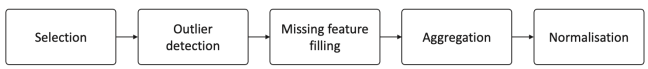

Figure 3: From left to right the steps that the data goes through as part of pre-processing.

those will likely have similar consumption patterns. Preferably communities are defined as smaller groups than on city level as that better mimics a real-world scenario where this disaggregation can be used. Houses that could not be put in a community were discarded.

The last step was to normalise the data. As the empirical rule was already applied, z-score normalisation was used on the household and community aggregates. Equation 2 shows how the z-score can be calculated, where x is the point, μ is the mean, and σ is the standard deviation. The normalisation shows how many standard deviations the point differs from the mean.

$$Z = \frac{x - \mu}{\sigma} \tag{2}$$

After all preprocessing was done, the input for the model existed of two normalised columns, one containing the aggregate of the community and the other containing the aggregate of the household.

4.3 Sequence-to-point

The sequence-to-point network is based on the one used in [22]. Compared to the model used for NILM we made modifications to the hyperparameters to allow for better performance of the model.

Seq2point defines a neural network to map sliding windows to points in the output. For a neural network the sliding windows $Y_t : t + W - 1$ get mapped to the midpoint x_r of the corresponding output window $X_t : t + W - 1$. Using this the loss function used for training can be defined as in equation 3, here θ_p is defined as the network parameters..

$$L_p = \sum_{t=1}^{T-W+1} \log p(x_r | Y_{t:t+W-1}, \theta_p) \tag{3}$$

The seq2point model uses a multilayer CNN architecture. Other architectures like RNN's or autoencoders can be used as well. For this research we used a CNN architecture as this is a proven method in [11; 22]. The input layer to model is a sliding window containing 499 points. The model contains 5 convolutional layers to model the non-linearity of the input. All these layers contain different filter sizes as can be seen in figure 2. The output layer is the predicted midpoint of the sliding window. Table 1 contains the remainder of the hyperparameters.

Name	Value
Batch size	200
Epochs	10
Learning rate	0.0001
Window length	499

Table 1: The hyperparameters used in the seq2point model.

4.4 Performance evaluation

To evaluate the models performance the Mean Absolute Error (MAE) and Root-Mean-Square Error (RMSE) are used. MAE gives an error in power at every point in time. x_t denotes the ground truth, $\hat{x}_t$ denotes the predicted power level of a household, and T is the total amount of data points. See equation 4.

$$MAE = \frac{1}{T} \sum_{t=1}^{T} |\hat{x}_t - x_t| \tag{4}$$

As a second metric RSME is used to see if the predictions are sensitive to outliers. See equation 5.

$$RMSE = \sqrt{\frac{\sum_{t=1}^{T} (\hat{x}_t - x_t)^2}{T}} \tag{5}$$

No baseline will be used for evaluation as the research was not about improving the performance of an algorithm in a specific domain. Rather it was showing that seq2point can be used for disaggregation from communities to households.

Error measure	Community	House 1	House 2	House 3	House 4	House 5	Overall
MAE	1	**9.568**	11.914	13.357	12.360	10.928	11.625 ± 1.444
	2	12.260	3.673	**2.780**	6.662	22.348	9.544 ± 8.060
	3	29.986	**4.763**	13.393	10.261	13.667	14.414 ± 9.414
	4	7.659	7.092	12.213	0.0	0.0	±
RMSE	1	**13.558**	16.041	19.243	18.115	15.101	16.411 ± 2.87
	2	14.536	4.976	**4.023**	8.750	32.237	12.904 ± 11.570
	3	42.672	**7.153**	18.969	14.354	18.792	20.388 ± 13.348
	4	10.699	10.753	16.322	0.0	0.0	0.0 ± 0.0

Table 2: Caption

5 Results

In this section, the results of preprocessing are discussed, and the results coming from the evaluation metrics are presented.

5.1 Data processing

The results might give rather big differences within communities, as can be observed by looking at the MAE in community three for houses one and two. One of the communities was discarded as its standard deviation was significantly higher than the others. The lowest data availability for a house was 98.88%, the highest data availability was 99.98%. Therefore the missing data got filled in during preprocessing.

5.2 Model results

Table 2 shows the performance in terms of MAE and RMSE. Highlighted are the best-performing results per community. The last column provides a summary showing the average and standard deviation within a community.

The results might give rather big differences within communities, as observed by looking at the MAE in community three for houses one and two. This happens even though the data is normalised before using it. To give a bit more feeling about the performance of the model, see table 3 the results of using seq2point for NILM from Zhang et al. (2018).

Appliance	Value
Kettle	7.439
Microwave	8.661
Fridge	20.894
Dishwasher	27.704
Washing machine	12.663
Overall	15.472 ± 7.718

Table 3: Appliance-level mean absolute error (MAE) in Watt trained by a seq2point.

It can be observed that our results give a better performance in terms of error measured by MAE. In figure 4, we can see the plot of the house. Most plots look similar to the one here. What we see is the model does not follow the ground truth, especially not at the peaks. The model achieves its results by staying around the mean value of the ground truth. Compare this to figure 4 from Zhang et al. (2018). There we can really see that the seq2point model recognises the pattern of the appliance.

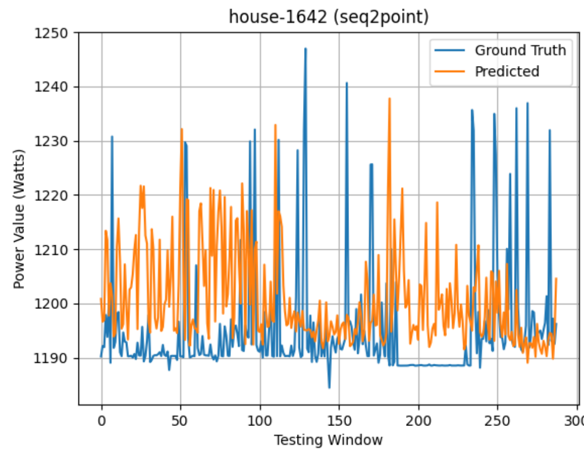

Figure 4: Ground truth and predicted value in Watt for house two of community one. The plot shows the first four days of the test set.

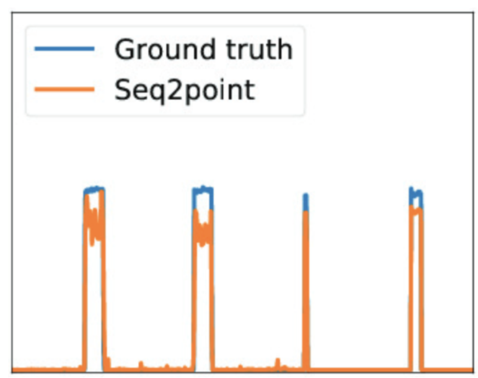

Figure 5: Perfomance of a seq2point model on the load signature of a kettle.

The RMSE is, in absolute terms, higher than the MAE. However, it does follow the trend of MAE. Signifying the model is not heavily affected by outliers. That aligns with what we see in figure 4.

6 Responsible Research

Disaggregating energy data from communities to households has the potential to become useful as an application. It provides more privacy as there would no longer be a need for smart meters in houses. Although the advantages, the ethical implications that it brings should be carefully considered.

Privacy is a benefit, but sensitive data is needed to train the models. This can only be done in a secure manner when all the data is anonymised. The data used in this research was already all anonymised. Care must also be taken because the data can contain more sensitive underlying information. For NILM, it was shown that it could be determined what TV channel someone is watching just from household consumption patterns [17]. If similar information can also be extracted from higher levels, entire communities could be profiled. Care must be taken to find the right balance between privacy and usefulness.

Furthermore, the information can be used in a discriminatory manner, especially when companies will charge customers based on disaggregated data. Companies should be reluctant when using the data in this way as biases can have a significant impact on their customers. Therefore clear guidelines should be made.

Lastly, there is an ethical implication concerning the repeatability of this research. Hence we have published the code [2] used, that together with the specified inputs is enough to confirm the result. The data can be found on the Pecan Street website.

7 Discussion

In this paper, we analysed how a seq2point architecture performs on the task of disaggregating energy consumption data from communities to households. This work is built on the model proposed by Zhang et al. (2018). In their work, the seq2point model is used to perform non-intrusive load monitoring.

As no research has been done in this specific domain, it is impossible to directly compare with other works. Nevertheless, compared to Zhang's work, the data performs better in terms of error. When looking at the graphs, we see that this comes from the model fitting to the mean of the data, so not actually learning the signature properly. We identified three potential causes for this.

Firstly, the size of the dataset might be too small. Compared to Zhang's work, we used an approximately seven times smaller dataset. In their work, they made use of the UK Domestic Appliance-Level Electricity (UK-dale) dataset[3].

Secondly, the 15-minute time steps lose a lot of the data. The energy consumption of short but heavy consumers might have been missed, even though those are the once that are characteristic. That is why in NILM research often appliances like kettles and microwaves are often used.

Another explanation is that the data does not follow distinctive enough patterns. In NILM, appliances have a recognisable load signature. For example, a kettle can be either ON or OFF, therefore it has two consumption levels in its signature. For households, there are many irregular levels making it harder to disaggregate.

[2] https://gitlab.tudelft.nl/lcavalcantesie/flexibily_aggregation_smart_grids

[3] https://jack-kelly.com/data/

Furthermore, it is important to acknowledge the limitations of this work. Memory has been a limiting factor in the possibilities of this research. Besides, the time limit restricted us in our possibilities. As such, the model from a different work has been used with limited hyperparameter tuning. Better optimisation might lead to better results.

8 Conclusions and Future Work

In this paper, we looked at the possibility of disaggregating energy consumption data from communities to gather information about consumption on a household level. This was done using a sequence-to-point network.

The model was trained on 15-minute interval data. The network achieves an average Mean Absolute Error of 11.592 Watt and an average Root-Mean-Square error of 16.135 Watt on the test set. These results are better than similar sequence-to-point networks applied in the domain of non-intrusive load monitoring. Although the performance is good, the network does not appear to capture the load signature, and rather it oscillates around the mean value.

Since the model does not manage to capture the load signature, it can not be of any significant use. The model could be improved by using data with shorter time intervals. Using a more extensive dataset also has the potential to improve the network.

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