Detection Of High Energy Consuming Appliances' Load Profiles Using Non-Intrusive Load Monitoring

Master Thesis Presentation by

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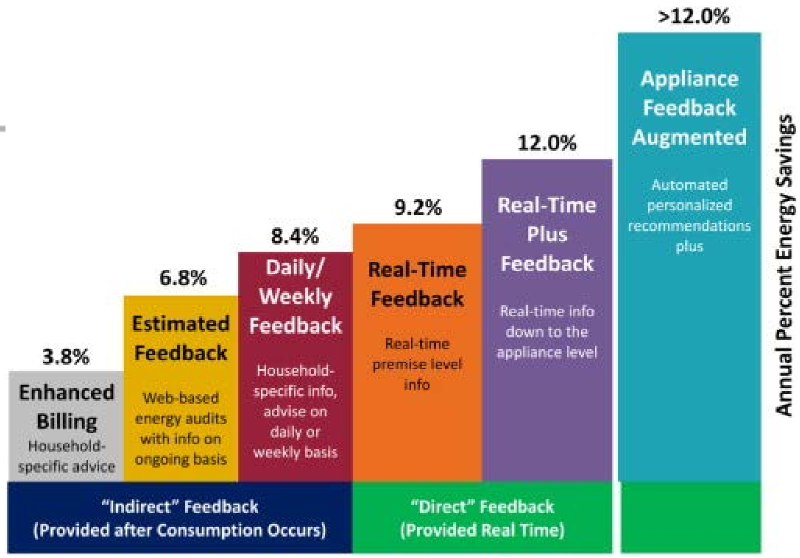
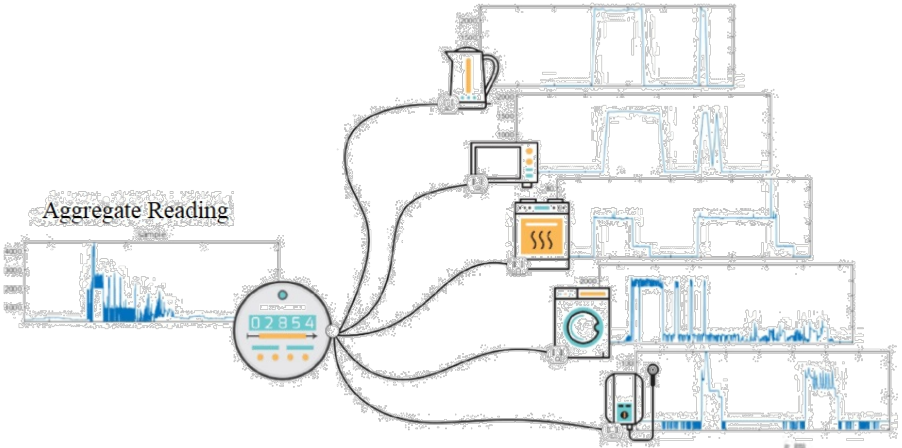
CONTENTS

Introduction

- Energy monitoring and real-time appliance level feedback can result in energy savings of upto 12%.



- Energy monitoring
  - Intrusive Load monitoring (ILM)
  - Non-intrusive load monitoring (NILM)



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Problem statement

- The aggregate energy consumed at a time t can be expressed as the sum of energy consumption of individual appliances.

$$Y_t = \sum_{i=1}^{m} X_{it} + \epsilon_t$$

- NILM can be used to predict whether a given appliance at time t is in ON state (S_{it}=1) or OFF state (S_{it}=0) :

$$S_{it} = \begin{cases} 1, & X_{it} > T_i \\ 0, & X_{it} < T_i \end{cases}$$

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Motivation

- Grid stability
- Conceive energy management strategies for optimal usage of appliances
- EV charging patterns are required for smart grid solutions like V2G
- Overall energy used by appliances can be determined

Introduction

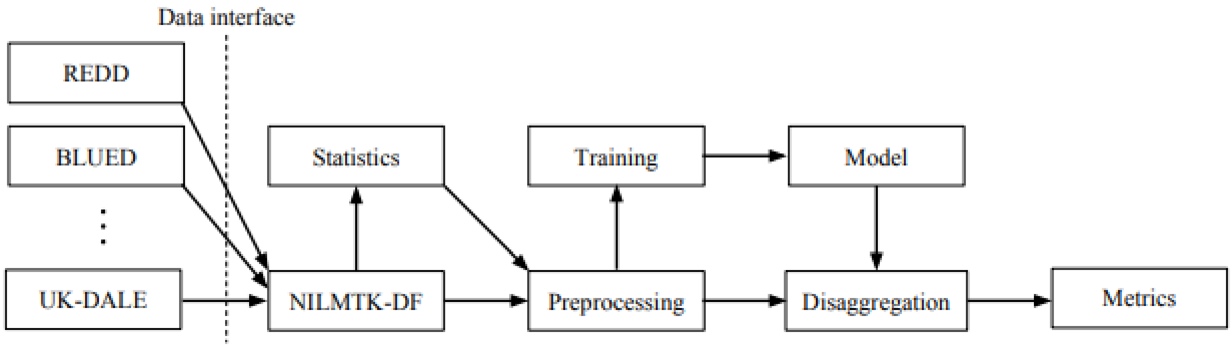
- Questions?

CONTENTS

- Introduction
- Approach
- Evaluation

NILMTK

- Open-source toolkit for comparitive analysis of NILM algorithms across various datasets.
- Provides a pipeline from datasets to evaluation metrics to lower the entry barrier for researchers.



Datasets

- Synpro dataset (synthetic)

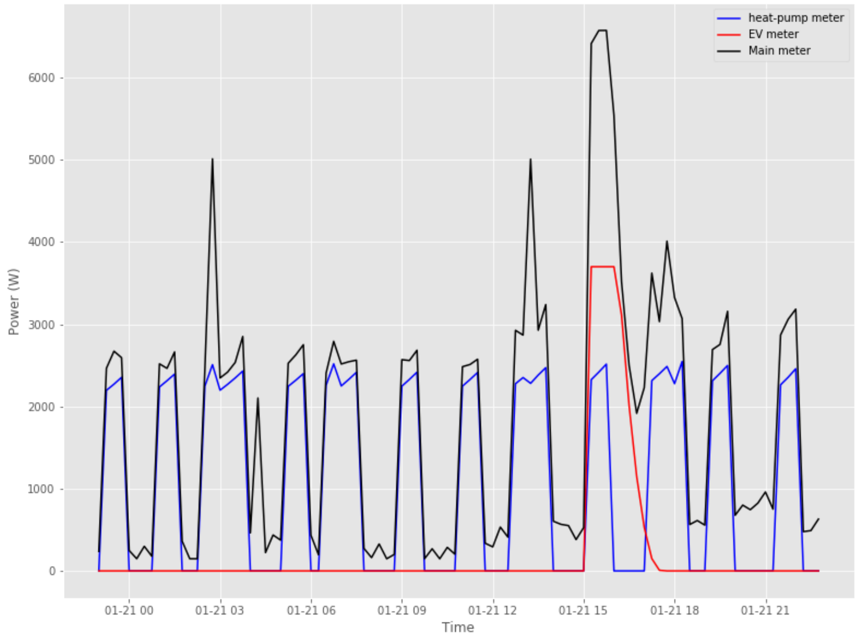
- Dataport dataset

Synpro Dataset

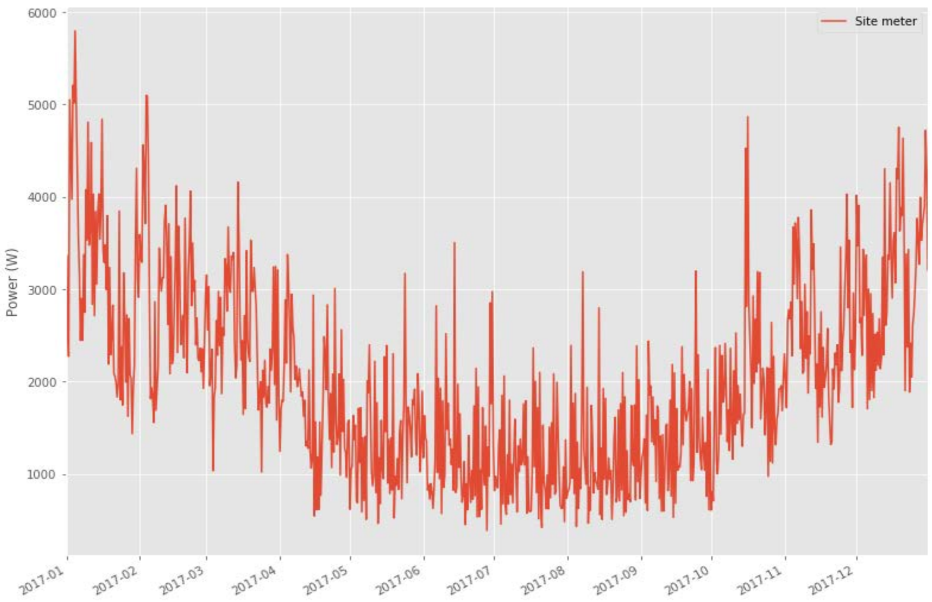
- The synthetic dataset is created using the Synpro tool which was developed at Fraunhofer ISE.
- Contains energy consumption time series of main meter, heat-pumps, EV charger and other appliances in a house.
- The sample rate used in this thesis is 15-minutes.

House Number	House Type	Number of Occupants	Charging Rate (kW)
1	Single-Family House	1	3.7
2	Single-Family House	2	7.2
3	Single-Family House	3	11
4	Single-Family House	4	3.7
5	Multi-Family House	2	7.2
6	Multi-Family House	2	3.7
7	Multi-Family House	4	11
8	Multi-Family House	4	7.2
9	Multi-Family House	6	11
10	Multi-Family House	6	3.7
11	Multi-Family House	8	11
12	Multi-Family House	8	7.2

Synpro Dataset



Energy consumption of the main meter, an EV charger and the heat-pump for a single day in house 4 of the Synpro dataset



Aggregate energy consumption in House 10 of Synpro dataset

Dataport Dataset

- Pecan Street Dataport database is the world’s largest publicly available resource for residential energy use data.
- They provide access to time-series energy consumption data for 75 houses.
- Only 6 houses contain energy consumption time-series for an EV charger for an entire year.
- These houses are located in Austin and California.
- The sample rate used in this thesis is 15-minutes.

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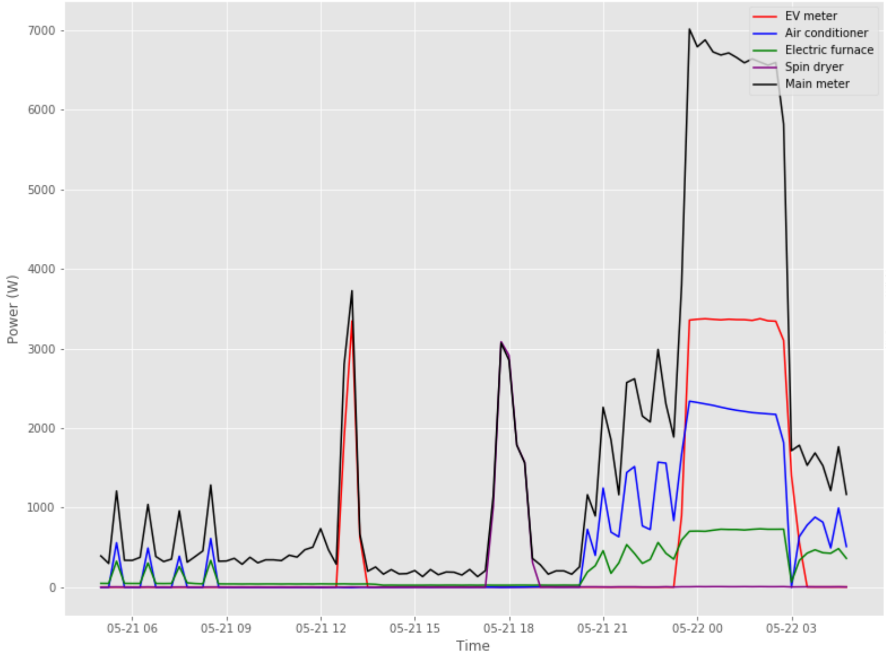
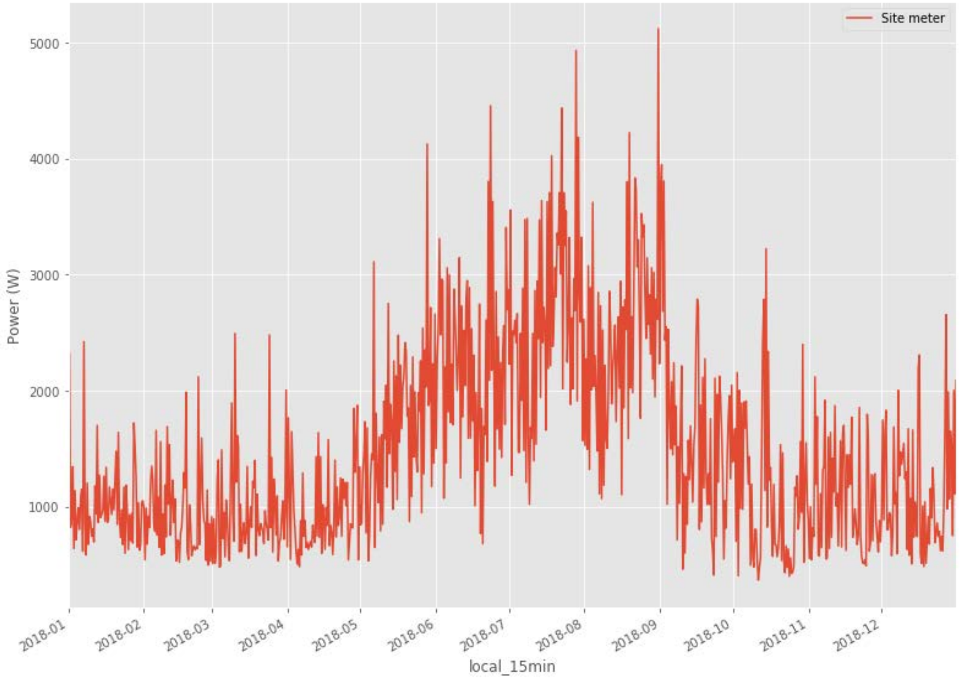
Dataport Dataset



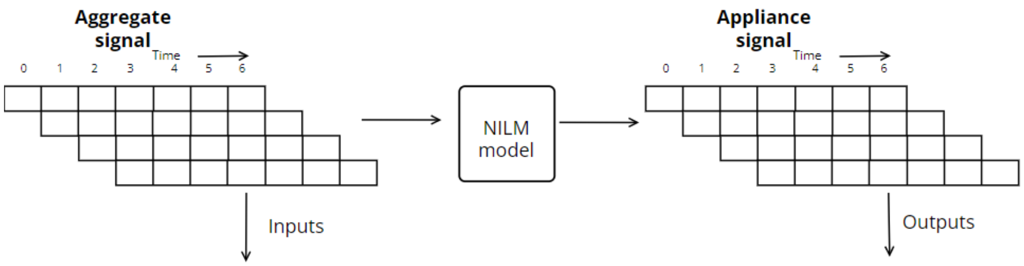
Energy consumption of the main meter, an EV charger and the air conditioner, electric furnace and spin dryer for a single day in house 3 of the dataport dataset



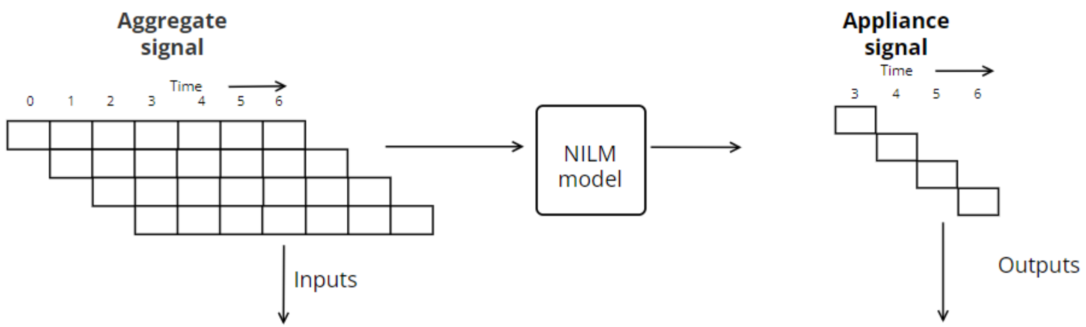
Aggregate energy consumption in House 1 of dataport dataset

Deep learning NILM algorithms

- Sequence-to-Sequence



- Sequence-to-Point



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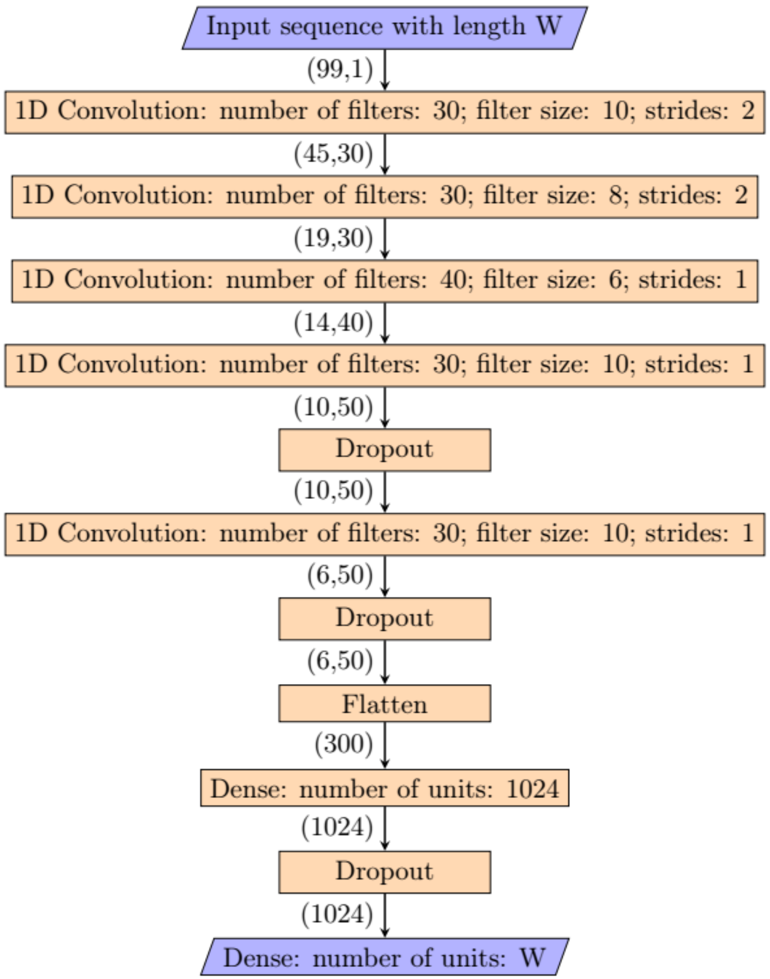
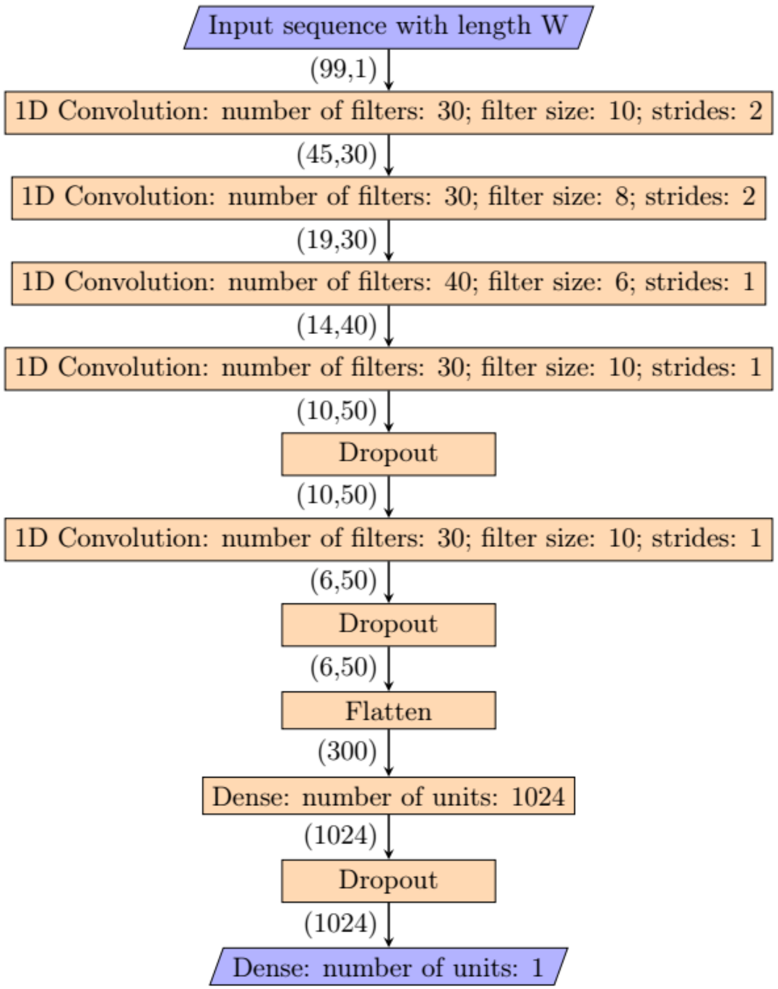
Seq2seq and Seq2point model architecture



Seq2seq Architecture



Seq2point Architecture

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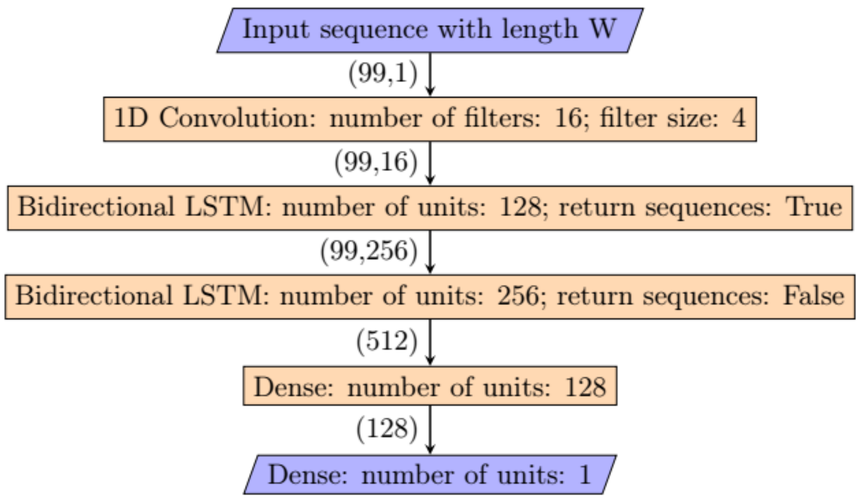
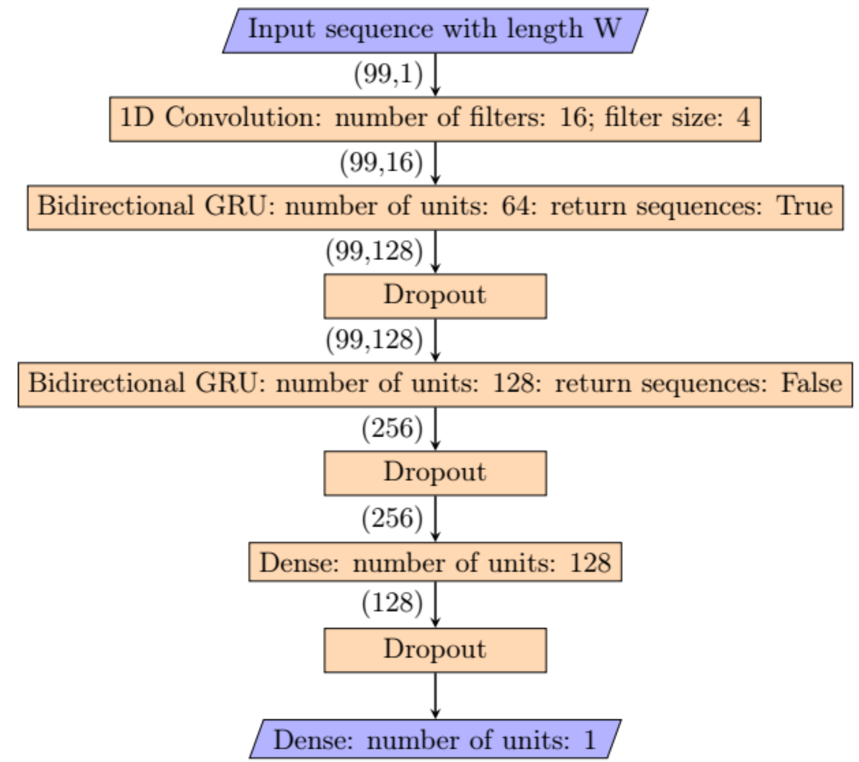
RNN and GRU model architecture

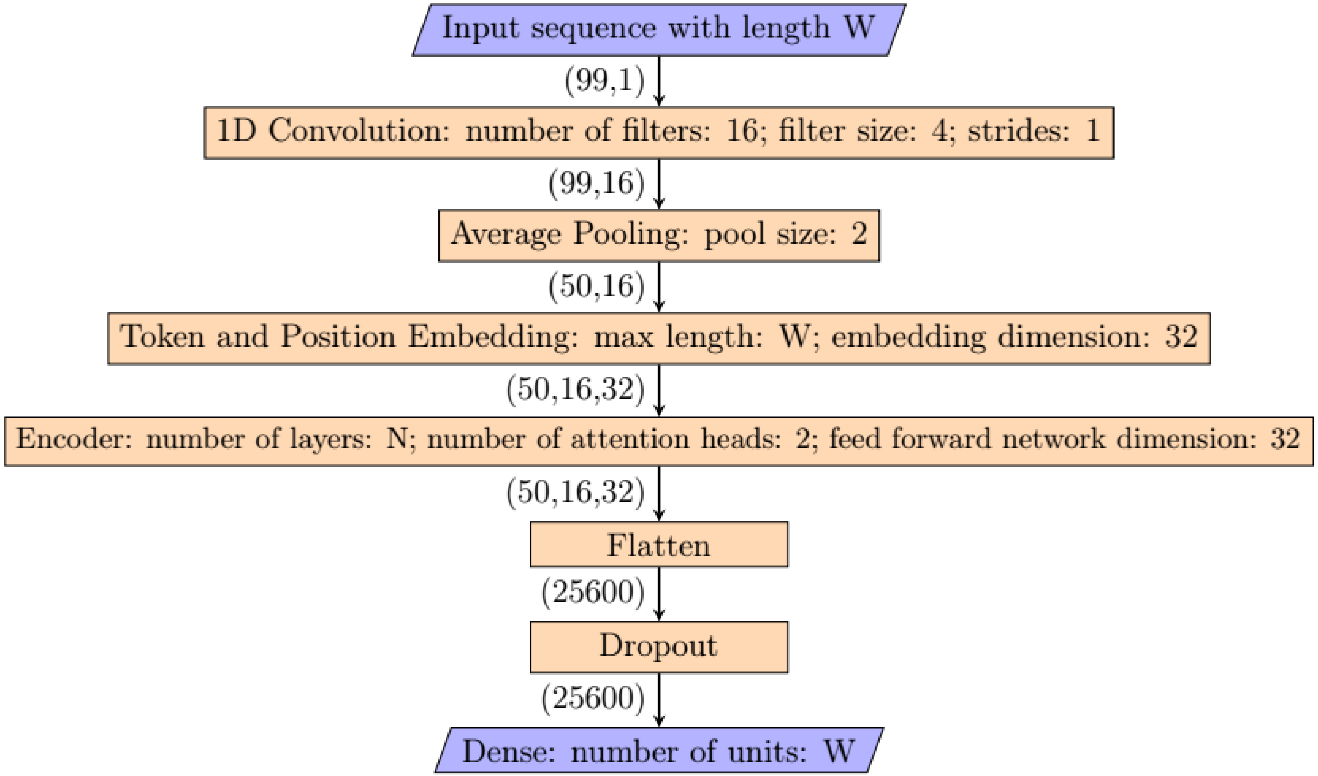


RNN Architecture



GRU Architecture

BERT model architecture



BERT architecture

Evaluation metric regression

- Mean Average Error (MAE):

$$MAE(y, \hat{y}) = \frac{1}{n_{sample}} \sum_{i=0}^{n_{sample}-1} |y_i - \hat{y}_i|$$

- Root Mean Square Error (RMSE):

$$RMSE(y, \hat{y}) = \sqrt{\frac{1}{n_{sample}} \sum_{i=0}^{n_{sample}-1} (y_i - \hat{y}_i)^2}$$

- Normalized Disaggregation Error (NDE):

$$NDE(y, \hat{y}) = \sqrt{\frac{\sum_{i=0}^{n_{sample}-1} (y_i - \hat{y}_i)^2}{\sum_{i=0}^{n_{sample}-1} (y_i)^2}}$$

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Evaluation metric classification

- Let the predicted value of energy consumed by a device by a model be P, the ground truth value of energy consumed by a device be G and threshold is T.
- At a particular timepoint the prediction is :
  - True Positive (TP) if P>T and G >T
  - True Negative (TN) if P<T and G<T
  - False Positive (FP) if P>T and G<T
  - False Negative (FN) if P<T and G>T
- Accuracy:

$$Accuracy = \frac{(TP + TN)}{(TP + FP + FN + TN)}$$

- Precision:

$$Precision = \frac{TP}{(TP + FP)}$$

- Recall

$$Recall = \frac{TP}{(TP + FN)}$$

- F1

$$F1 = 2 * \frac{(Precision * Recall)}{(Precision + Recall)}$$

Approach

- Questions?

CONTENTS

- Introduction
- Approach
- Evaluation

Setup

- Training and testing done on the same house

- Train dataset- January-September
- Test dataset – October-December

- Early stopping – 15 epochs

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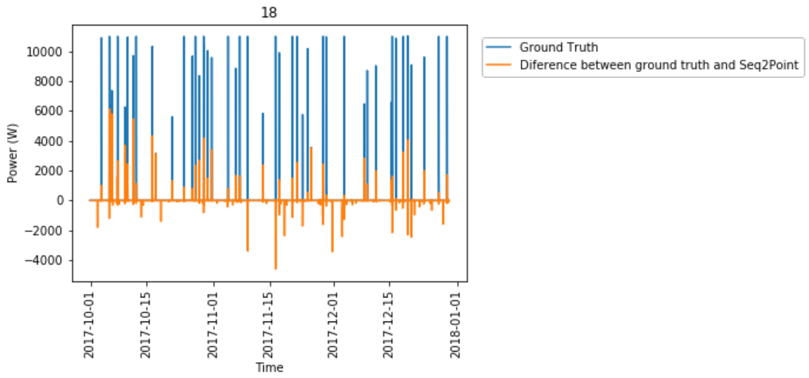
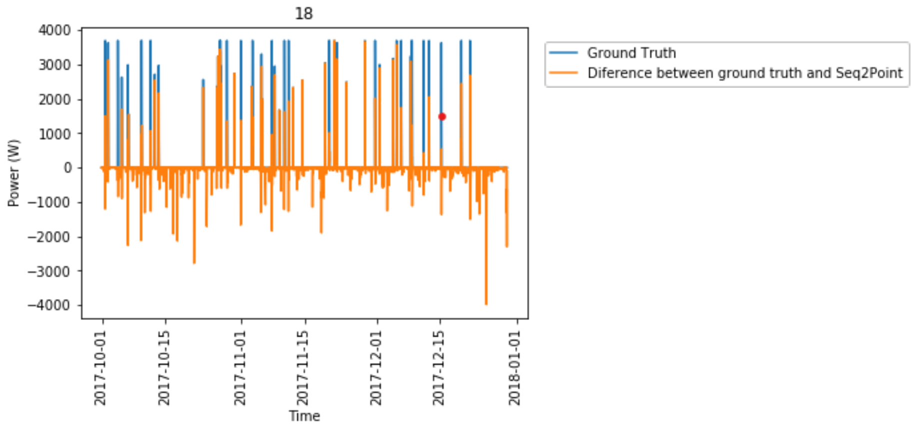
1.Comparison between various algorithms using Synpro dataset for EV charger energy prediction

House	EV charger (NDE)						
	RNN	Seq2seq	Seq2point	GRU	BERT-1	BERT-4	BERT-6
1	0.406	0.321	**0.315**	0.434	0.452	0.408	0.453
2	0.417	0.328	**0.285**	0.394	0.374	0.367	0.335
3	0.601	0.298	**0.238**	0.242	0.259	0.249	0.259
4	0.672	**0.585**	0.597	0.648	0.701	0.697	0.652
5	0.614	0.311	**0.306**	0.361	0.329	0.332	0.302
6	0.765	0.597	**0.591**	0.621	0.633	0.628	0.614
7	0.518	0.335	**0.253**	0.319	0.281	0.288	0.261
8	0.751	0.555	0.556	0.579	0.530	0.585	**0.537**
9	0.542	0.329	**0.263**	0.320	0.311	0.345	0.326
10	0.641	0.442	**0.441**	0.611	0.587	0.562	0.562
11	0.752	0.305	**0.259**	0.314	0.345	0.344	0.346
12	0.607	0.416	**0.403**	0.491	0.457	0.438	0.416

1.Comparison between best and worst performing Seq2point model for EV charging power prediction





Results of Seq2point algorithm in house 3 of Synpro dataset on EV charging power prediction.

Results of Seq2point algorithm in house 4 of Synpro dataset on EV charging power prediction.

1.Comparison between various algorithms using Synpro dataset for heat-pump energy prediction

House	Heat-pump (NDE)						
	RNN	Seq2seq	Seq2point	GRU	BERT-1	BERT-4	BERT-6
1	0.437	0.273	**0.141**	0.148	0.453	0.395	0.403
2	0.688	0.300	**0.201**	0.209	0.533	0.516	0.464
3	0.625	0.254	0.149	**0.133**	0.492	0.488	0.499
4	0.544	0.268	**0.162**	0.164	0.531	0.474	0.466
5	0.738	0.238	0.141	**0.124**	0.446	0.396	0.419
6	0.612	0.239	**0.156**	0.165	0.495	0.425	0.424
7	0.473	0.251	0.163	**0.146**	0.537	0.489	0.520
8	0.716	0.318	0.244	**0.229**	0.583	0.520	0.572
9	0.594	0.334	**0.252**	0.256	0.609	0.554	0.545
10	0.626	0.316	**0.234**	0.237	0.595	0.552	0.538
11	0.546	0.299	**0.219**	0.224	0.548	0.547	0.552
12	0.484	0.393	**0.310**	0.321	0.583	0.555	0.559

2. Comparison between various algorithms using Dataport dataset

House	EV charger (NDE)						
	RNN	Seq2seq	Seq2point	GRU	BERT-1	BERT-4	BERT-6
1	0.317	0.256	**0.202**	0.393	0.415	0.388	0.453
2	0.399	0.306	**0.229**	0.253	0.417	0.369	0.335
3	0.503	0.404	**0.371**	0.398	0.478	0.444	0.438
4	0.364	0.310	**0.250**	0.262	0.316	0.290	0.302
5	1.12	1.03	1.14	1.046	1.072	**1.009**	1.041
6	0.689	0.539	**0.524**	0.608	0.633	0.538	0.561

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3. Effect of using multi-input models with weather (temperature) as additional input on the Synpro dataset.

House	EV charger (NDE)				Heat-pump (NDE)			
	Seq2point		BERT		Seq2point		BERT	
	multi-input	original	multi-input	original	multi-input	original	multi-input	original
1	0.258	0.315	0.394	0.408	0.134	0.141	0.205	0.403
2	0.253	0.285	0.399	0.335	0.178	0.201	0.258	0.464
3	0.175	0.238	0.331	0.249	0.142	0.149	0.217	0.499
4	0.500	0.597	0.648	0.652	0.136	0.162	0.218	0.466
5	0.230	0.306	0.339	0.302	0.116	0.141	0.205	0.419
6	0.52	0.591	0.647	0.614	0.133	0.156	0.210	0.424
7	0.211	0.253	0.360	0.261	0.144	0.163	0.232	0.520
8	0.440	0.556	0.551	0.537	0.227	0.244	0.330	0.572
9	0.225	0.263	0.406	0.311	0.236	0.252	0.335	0.545
10	0.375	0.441	0.591	0.562	0.205	0.234	0.300	0.538
11	0.234	0.259	0.371	0.344	0.188	0.219	0.317	0.552
12	0.367	0.403	0.476	0.416	0.287	0.310	0.392	0.559

4. Effect of using multi-output models by using the same model to predict more than one appliance at a time on the Synpro dataset.

House	EV charger (NDE)				Heat-pump (NDE)			
	Seq2point		BERT		Seq2point		BERT	
	multi-output	original	multi-output	original	multi-output	original	multi-output	original
1	0.319	0.315	0.459	0.408	0.168	0.141	0.408	0.403
2	0.291	0.285	0.345	0.335	0.222	0.201	0.466	0.464
3	0.264	0.238	0.287	0.249	0.185	0.149	0.488	0.499
4	0.601	0.597	0.644	0.652	0.180	0.162	0.472	0.466
5	0.303	0.306	0.323	0.302	0.147	0.141	0.418	0.419
6	0.588	0.591	0.645	0.614	0.167	0.156	0.443	0.424
7	0.323	0.253	0.300	0.261	0.178	0.163	0.494	0.520
8	0.555	0.556	0.525	0.537	0.267	0.244	0.555	0.572
9	0.309	0.263	0.435	0.311	0.260	0.252	0.586	0.545
10	0.445	0.441	0.564	0.562	0.247	0.234	0.564	0.538
11	0.331	0.259	0.367	0.344	0.241	0.219	0.540	0.552
12	0.419	0.403	0.424	0.416	0.330	0.310	0.586	0.559

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5. Effect of Converting the BERT model to BERT2Point model.

House	EV charger (NDE)		Heat-pump (NDE)	
	BERT2point	Original BERT	BERT2point	Original BERT
1	0.529	0.408	0.449	0.403
2	0.388	0.335	0.521	0.464
3	0.260	0.249	0.540	0.499
4	0.707	0.652	0.495	0.466
5	0.400	0.302	0.546	0.419
6	0.662	0.614	0.546	0.424
7	0.325	0.261	0.520	0.520
8	0.574	0.537	0.558	0.572
9	0.348	0.311	0.569	0.545
10	0.600	0.562	0.681	0.538
11	0.359	0.344	0.560	0.552
12	0.470	0.416	0.605	0.559

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6.Performance of the Seq2Point and BERT algorithms in terms of NDE when tested on unseen house

Serial Number	House Train	House Test	EV charger (NDE)		Heat-pump (NDE)	
			Seq2point	BERT	Seq2point	BERT
1	1	4	0.714	0.902	0.220	0.524
2	4	1	0.485	0.526	0.180	0.511
3	5	8	0.655	0.576	0.277	0.565
4	5	12	0.519	0.611	0.405	0.724
5	6	10	0.679	0.676	0.312	0.635
6	7	9	0.285	0.319	0.261	0.594
7	7	11	0.325	0.433	0.236	0.588
8	8	5	0.533	0.526	0.209	0.493
9	8	12	0.531	0.574	0.342	0.615
10	9	7	0.304	0.293	0.202	0.554
11	9	11	0.232	0.524	0.232	0.524
12	10	6	0.671	0.714	0.250	0.606
13	11	7	0.442	0.346	0.206	0.605
14	11	9	0.465	0.326	0.265	0.579
15	12	5	0.460	0.414	0.300	0.641
16	12	8	0.610	0.543	0.279	0.596

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7.Effect of training on both datasets and testing on Dataport dataset

House Dataport	House Synpro	EV charger (NDE)			
		Seq2point	Seq2point-old	BERT	BERT-old
1	6	0.195	0.202	0.886	0.388
2	6	0.277	0.229	0.849	0.335
3	6	0.381	0.371	0.826	0.438
4	1	0.227	0.250	0.318	0.290
5	4	1.120	1.140	0.961	1.009
6	10	0.509	0.524	0.827	0.538

8.Performance of Seq2Point and BERT algorithms in electric vehicle charging event detection

House	Seq2point		BERT	
	Accuracy	F1	Accuracy	F1
1	99.0%	0.902	97.6%	0.794
2	99.0%	0.911	97.9%	0.821
3	99.8%	0.931	99.6%	0.885
4	98.5%	0.742	97.7%	0.628
5	99.7%	0.946	99.2%	0.843
6	97.6%	0.708	96.1%	0.843
7	99.6%	0.903	99.3%	0.825
8	98.6%	0.770	98.0%	0.695
9	99.4%	0.907	98.7%	0.768
10	96.5%	0.861	87.9%	0.637
11	99.5%	0.88	99.2%	0.795
12	98.9%	0.851	97.9%	0.734

Conclusion

- Seq2point outperforms other NILM algorithms on both datasets.
- Additional weather data improved the performance of the Seq2point and BERT models in predicting energy consumed by heat-pump.
- Multi-output models can be used to save training time.

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Thank You!

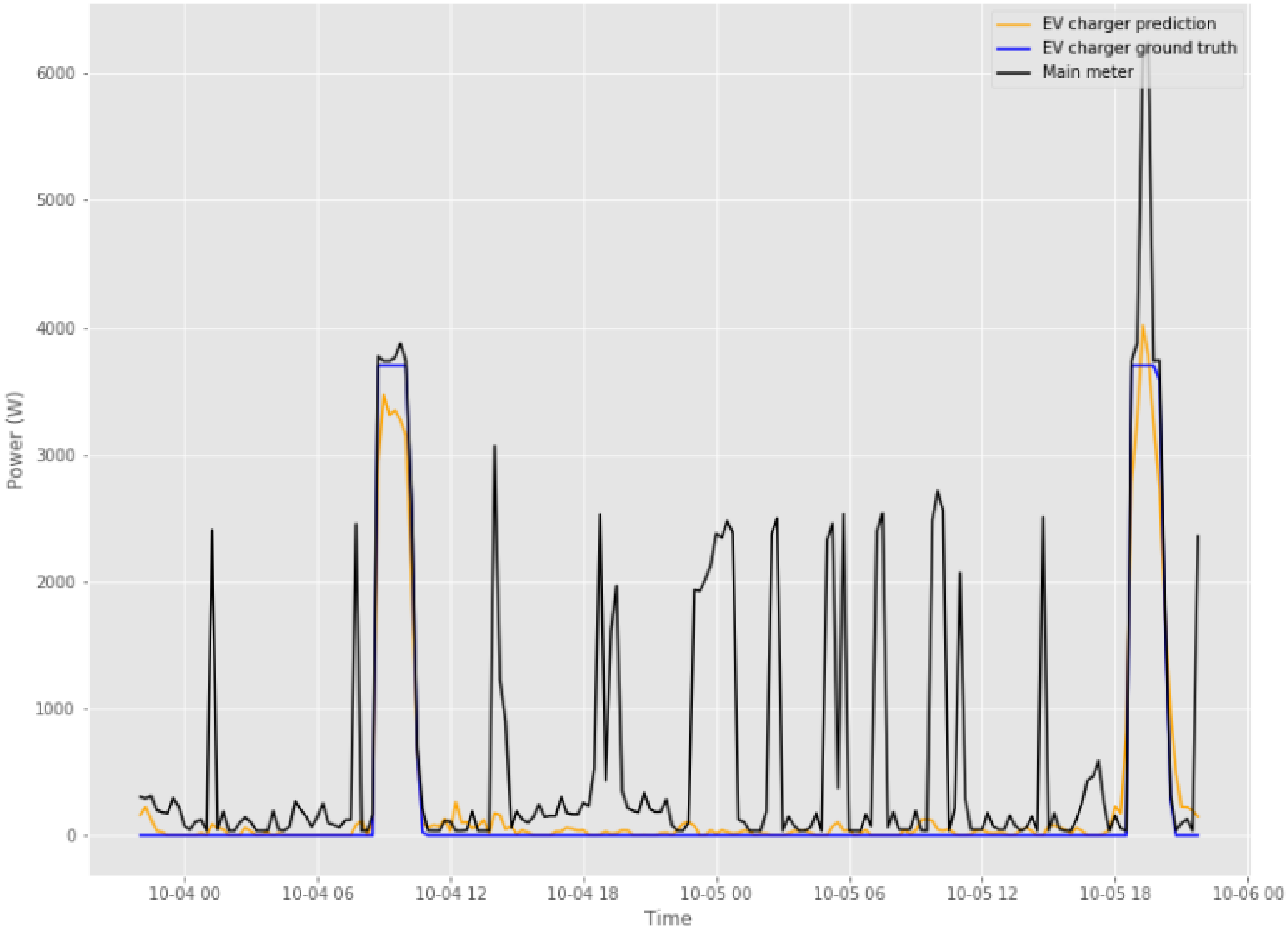
Evaluation

- Questions?

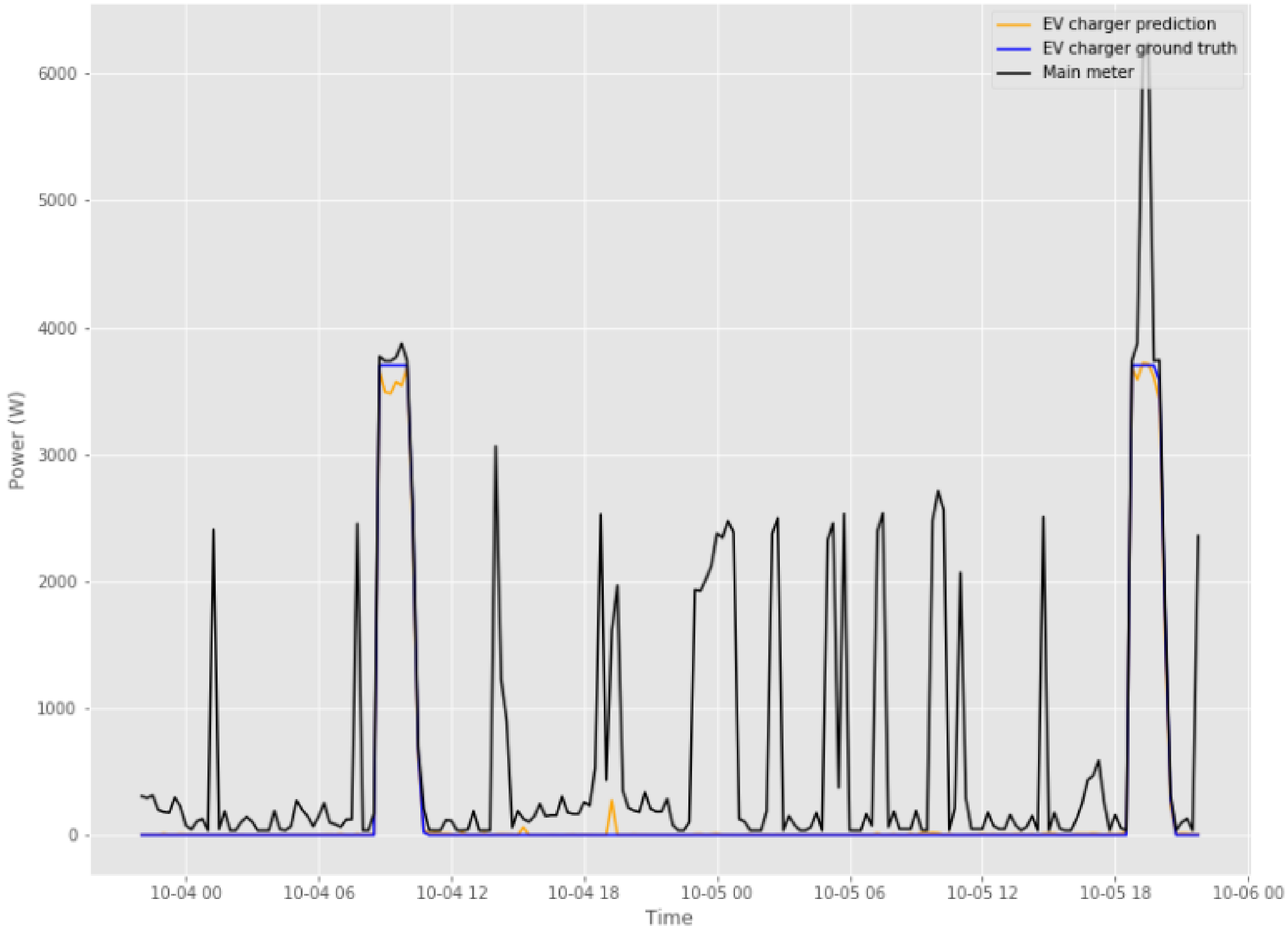
Training time

Algorithm	Number of epochs	Average time taken per epoch	Average total training time
Seq2seq	50	1 Second	50 Seconds
Seq2point	50	1 Second	50 Seconds
RNN	50	10 Seconds	500 Seconds
GRU	50	67 Seconds	3350 Seconds
BERT with 1 encoder layer	50	24 Seconds	4800 Seconds
BERT with 4 encoder layers	50	47 Seconds	9400 Seconds
BERT with 6 encoder layers	50	71 Seconds	14200 Seconds

BERT EV charger single day predictions



Seq2point EV charger single day predictions



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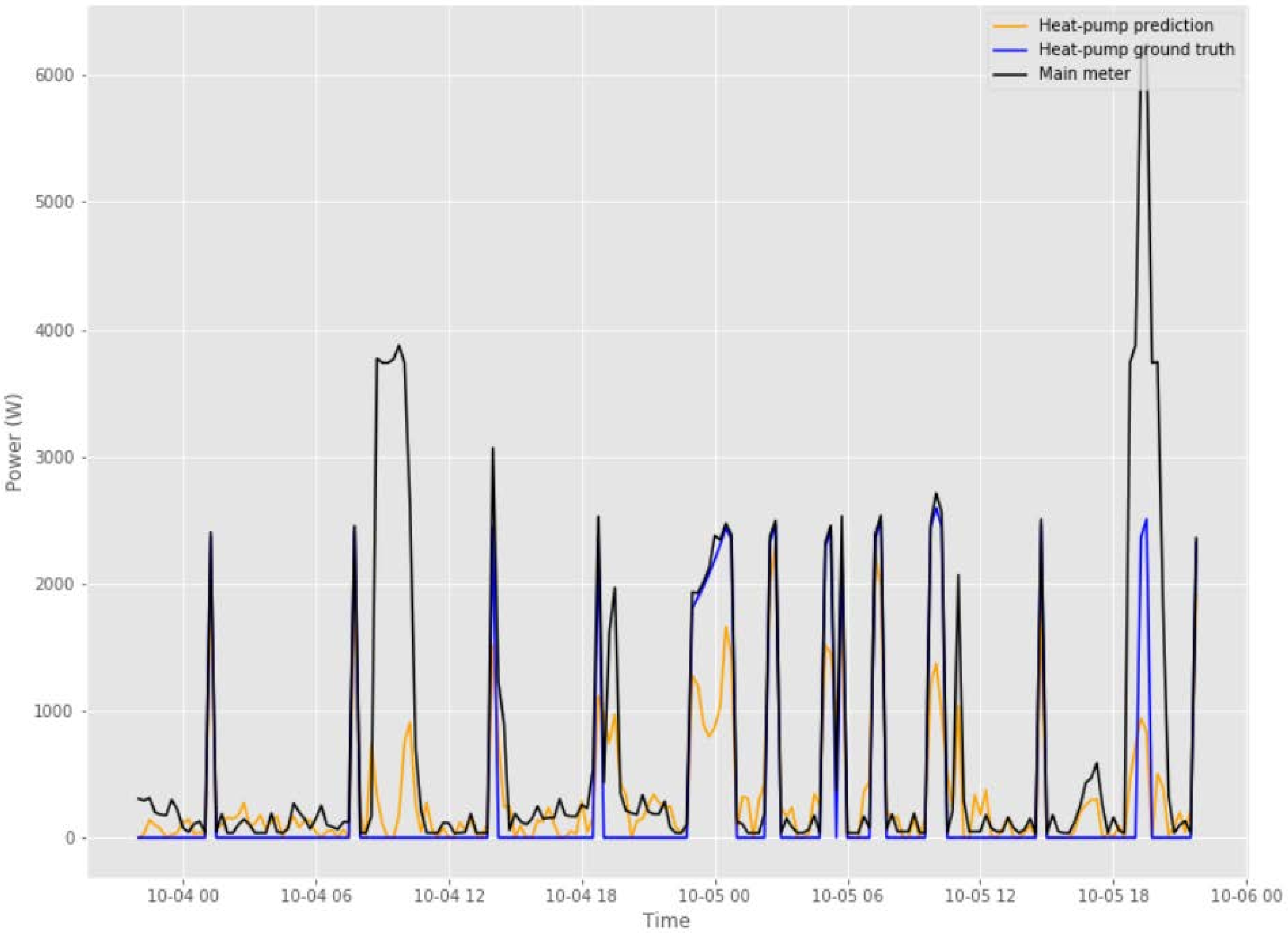
BERT heat-pump single day predictions



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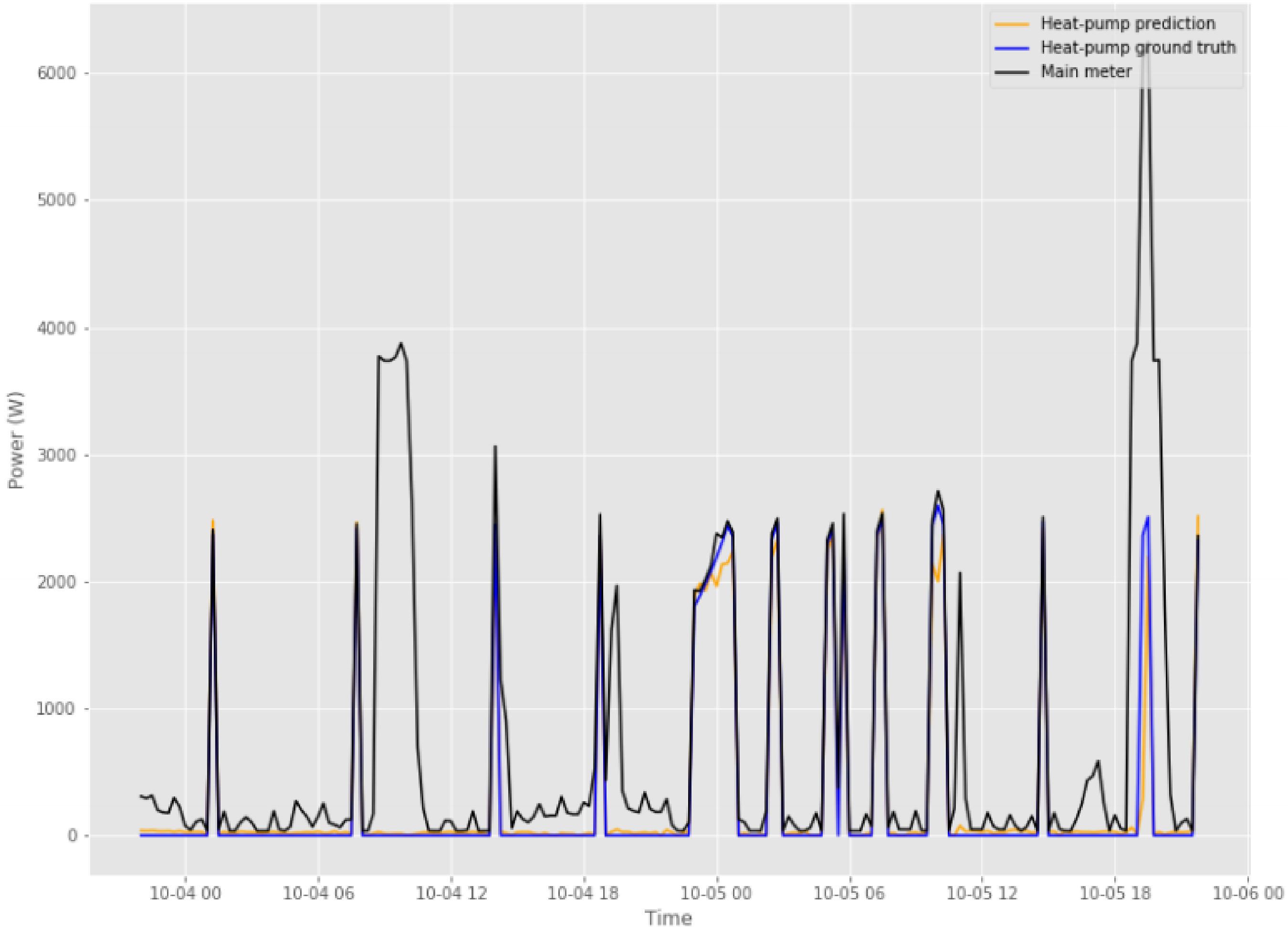
Seq2point heat-pump single day predictions



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