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Recognition and prediction of heat pump state of operation from smart meter data

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THERMAL ENERGY STORAGE

Motivation

An important share of the heat demand in Switzerland is already provided by heat pumps. However, it is necessary to speed up this transition from non-efficient and polluting heating systems to more sustainable ones.

Traditional demand side management (DSM) techniques still in use today, consist of deactivating loads, such as heat pumps, during peak consumption times. Novel coordinated control of larger numbers of loads opens the possibility of new DSM business cases. However, this requires understanding of the operation of the HP components to avoid disrupting their duty cycles and potentially damaging the equipment.

Methods for recognition of heat pump operating modes

As the roll out of digital-meters continues practically in every utility, numerous research and innovation projects have looked at utilizing these data to better manage loads (DSM). When it comes to HPs within those loads behind the meter, aspects studied are related their control, identification and characterization.[1,2]

Our work concerns the identification of the HP state of operation. For this purpose, methods developed in previous work make use of

- *classical* machine learning: feature engineering, dimensionality reduction, clustering;
- Bayesian change point detection approaches; and
- deep learning

The *classical* approach consists, essentially, of two steps (1) cycle recognition (i.e. cycles may be of different durations), and (2) classification of each cycle into one of the possible HP states. The classification takes places in a feature space corresponding to various summary metrics of each cycle. On the other hand, when applying artificial neural networks (NN), the cycle duration is fixed and the NN is trained to learn the mapping between the HP cycle-power consumption time series and the labels indicating the operating state. As illustrated in Figure 1, in this work we abstract the different HP operating states into the most relevant ones

- off,
- space heat, and
- hot water

Other common approaches for time series classification such as dynamic time wrapping, longest common subsequence, or clustering have not yet been applied.

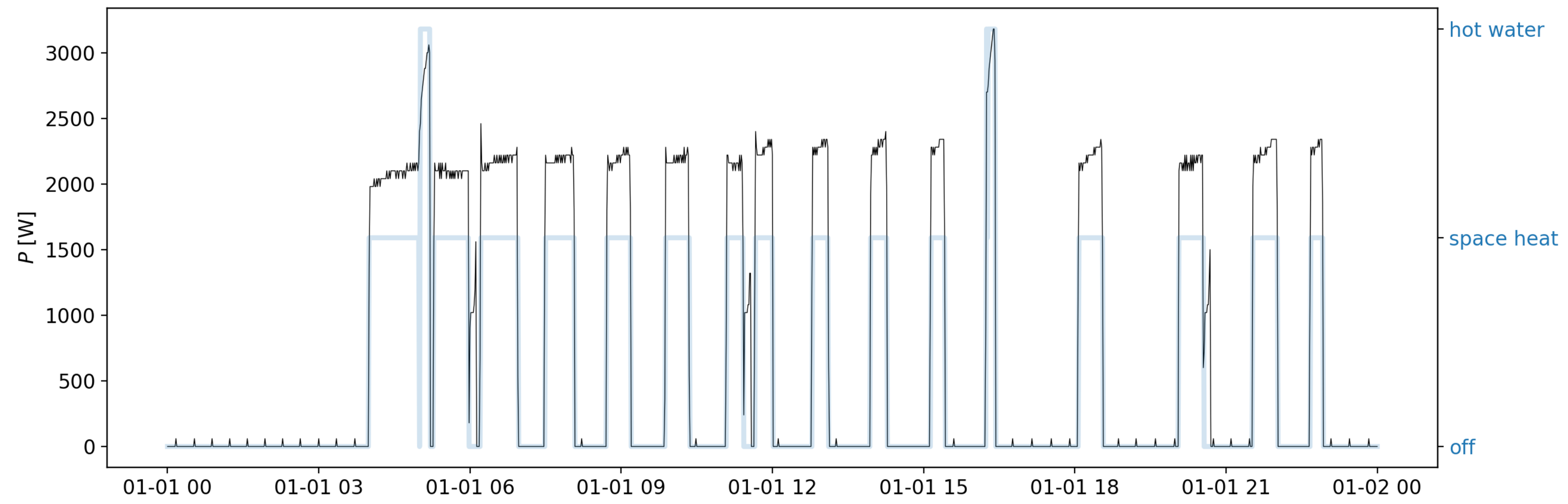

Figure 1. Load profile and states of an air source HP (PLZ92242) from WP Monitor data set

Our focus is on recognizing the operational state of heat pump (HP) systems with algorithms that can potentially by applied near-real time to inform control decisions, we investigate one dimensional convolutional NNs. Compared to recurrent NN, which have feedback loops between output and input, low complexity convolutional neural networks (CNNs) have been shown better performance on sequence modelling tasks.[3,4] A simple model of a NN can serve as good baseline for more advance deep learning models, recently such 1D-CNN type of models have been applied to electricity load forecasting[5], and prediction of energy efficiency of domestic cooling systems.[6] For the implementation of the models we use TensorFlow (v2.2.0) through its high-level application interface Keras[7].

Data sets and models

In the context of this work, we explore several datasets, Table 1 describes three of them. The HSLU data is collected for load disaggregation research, while the NTB Buchs and the WP Monitor data concern dedicated HP research activities aimed at evaluating the efficiency of HP systems. Thus, besides the energy consumption data typically recorded by digital energy meters; temperature, volumetric flow, and power consumption are recorded by dedicated sensors. Moreover, binary variables indicating the operation of key components such as compressors, pumps, electrical backup heaters, cooling circuits, and storage tanks are provided. Here, we use those variables to label data with the corresponding state of operation. Figure 1 shows the compressor power consumption and state of operation of an air source HP during a winter day.

Table 1. Three load monitoring data sets that include heat pump data.

	Description
NTB Buchs [8]	10-second resolution, 13 HP systems (air-water, brine-water, variable speed, systems with cooling, new and renovated systems), duration 3 years.
WP Monitor [9]	1-minute resolution, 87 HPs (direct evaporation systems, ground source HPs, and variable speed compressor HPs), duration 3 years
HSLU [10]	5-minute resolution, power consumption data from 3 HPs (air-water, and brine-water), duration 1.5 up to 3.5 years

State encodings. From the NTB Buchs and WP monitoring data is possible to derive *ground truth* information about the state of operation. We apply the following steps: (1) define a set of N components, e.g. compressor, pumps, and electrical backup heater; (2) select binary variables b_i that describe the state of each component i at each time step; where $b_i = 0$ and $b_i = 1$ stand for component i off and on respectively; (3) given the state of each component i in b_i, encode the HP state as a concatenation of them; and (4) from the space of states $2^{|N|}$ abstract the states $S = \{\text{off}, \text{space heat}, \text{hot water}\}$ on the basis of the engineering understanding of the heat pump. Table 2 shows summary statistics of the encoded states for a year of operation, as expected states have distinctive statistical features.

Table 2. Compressor power [W] summary statistics per state of ground source HP during 2011 from WP Monitor data set.

	count	mean	std	min	25%	50%	75%	max
off	425884	0	1	0	0	0	0	180
space heat	81284	1199	169	60	1200	1200	1260	2160
hot water	18432	1841	287	60	1680	1920	2040	2280

Modelling and prediction. Our model takes as input compressor power consumption X and outputs states S, it consists of stacked 1D-convolutional layers n_L with a given number of filters, filter size k_s, causal padding, and dilation rate r. The model parameters are learned with Adam optimizer to minimize mean squared error. Learning rate 0.1, 60 epochs with batch size 120 yield reasonable results, however for some experiments these maybe adjusted to speed up convergence or avoid overfitting. Evaluation of model prediction is done calculating the accuracy of the predictions compared to the true states. We test different model configurations (n_L, k_s, r) and look a head horizons (hours to day-ahead) to illustrate their impact on forecast accuracy and on computing resources (training and inference time, and model size).

Final remarks and outlook

Several data sets are available to study the behaviour of heat pumps as seen from the grid, but dedicated monitoring campaigns are valuable to observe the behaviour behind the meter. We use these data to encode the heat pump state of operation, and evaluate the performance of one dimensional convolutional neural networks (1D-CNNs) with different configurations to predict the time evolution of the states. As expected, sudden changes of states are hard to predict correctly. However, training these networks with only a couple of hours of training data, on a laptop takes less than a minute for the deepest network (4 convolutional layers) we tested. Thus, it seems feasible to run them in an *online* fashion. Training on a full year of 1-minute data, for the deepest network takes up to 20 minutes. Next steps in our research involve the evaluation of models to predict energy consumption at different levels of aggregation.

[1]Fei, H., Kim, Y., Sahu, S., Naphade, M., Mamidipalli, S.K., Hutchinson, J.: Heat pump detection from coarse grained smart meter data with positive and unlabeled learning. In: Proceedings of the 19th ACM SIGKDD International Conference on Knowledge Discovery and Data Mining, pp. 1330–1338 (2013)
[2]Le Ray, G., Christensen, M.H., Pinson, P.: Detection and characterization of domestic heat pumps. In: 2019 IEEE Milan PowerTech, pp. 1–6 (2019). IEEE
[3]Bai, S., Kolter, J.Z., Koltun, V.: An empirical evaluation of generic convolutional and recurrent networks for sequence modeling. arXiv preprint arXiv:1803.01271 (2018)
[4]Dürr, O., Sick, B., Murina, E.: Probabilistic Deep Learning with Python, Keras and TensorFlow Probability. Manning Publications Co., New York, NY (2020)
[5]Lang, C., Steinborn, F., Steffens, O., Lang, E.W.: Electricity load forecasting–an evaluation of simple 1d-cnn network structures. arXiv preprint arXiv:1911.11536 (2019)
[6]Kittisarakul, S., Banjerdpongchai, D.: Convolutional neural networks for predicting energy efficiency of air conditioning systems. In: 2020 17th International Conference on Electrical Engineering/Electronics, Computer, Telecommunications and Information Technology (ECTI-CON), pp. 792–795 (2020). IEEE
[7]`https://www.tensorflow.org/` and `https://keras.io/about/`