DISTRHEAT

Digital intelligent and scalable control for renewables in heating networks

Deliverable 4.2

Report on the development of the statistical load model

Stavros Vouros

May 5th, 2022

This project has received funding in the framework of the joint programming initiative ERA-Net Smart Energy Systems' focus initiative Integrated, Regional Energy Systems, with support from the European Union's Horizon 2020 research and innovation programme under grant agreement No 775970.

Document status

Deliverable No.:	4.2
Deliverable title:	Report on the development of the statistical load model
Version:	1
Date created:	May 4th, 2022
Date updated:	May 5th, 2022
Date submitted:	May 10th, 2022

Document preparation

	Date	Name	Organization
Authored by:	May 5th, 2022	Stavros Vouros	Mälardalen University
Reviewed by:	May 5th, 2022	Konstantinos Kyprianidis	Mälardalen University
Approved by:	May 5th, 2022	General assembly	

Document sensitivity

Moderately sensitive

Available status options:

- Not sensitive
- Moderately sensitive
- Sensitive
- Highly sensitive & confidential

Table of Contents

Executive summary

This document describes the development of the physics-informed data-driven model for heat load prediction. A description of the main data streams and substation layout is provided. The model architecture is presented in terms of real-time data handling. The calibration of the model is briefly explained for the identification of the training and prediction horizons. A verification of the model is included with respect to measured data from a representative substation in Västerås, Sweden. Aspects related to future use of the model are discussed.

1. Introduction

A physics-informed data-driven model has been developed for the prediction of heat load and indoor temperature in district heating substations. Models based purely on physics are complex to develop. Furthermore, it is challenging to generalize them for application on different buildings. Purely data-driven approaches struggle to predict outside the training regions. The proposed approach combines the benefits of both worlds aiming at large-scale utilization within smart control algorithms.

2. Model description

2.1. Data streams

The heat load model is using the data coming from the standard meters of the heat exchanger and the building. An overview of facility is presented in Fig. 1.

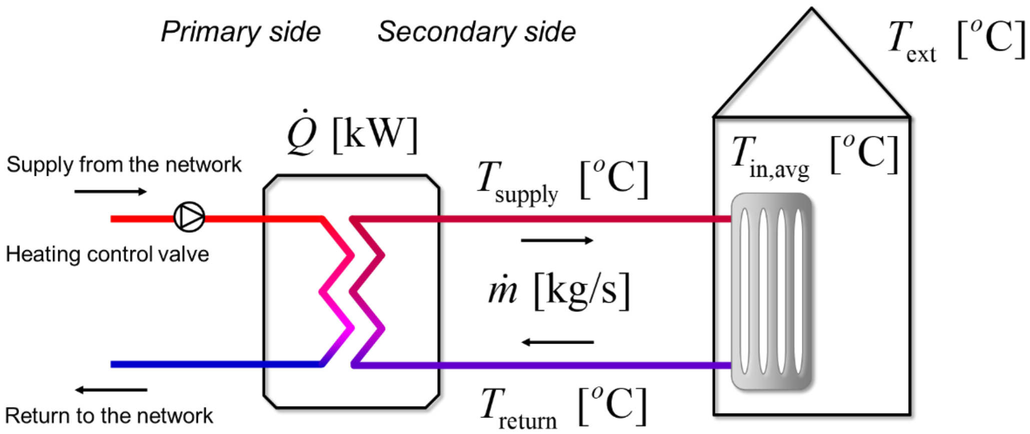

Figure 1: Overview of facility metering system

Specifically, the parameters used within the model include:

- Water temperatures at the heat exchanger, both from the primary and secondary side of the installation
- Water mass flows at the heat exchanger, both from the primary and secondary side of the installation
- Control valves for heating and domestic hot water
- Apartment indoor temperatures
- Outdoor temperature

The average indoor temperature is used as a driver for the comfort response of the entire building. This is done for two reasons:
(a) Individual control of apartment indoor temperatures is not a commonly used solution in Sweden; therefore, extensive installation of extra hardware would be required.
(b) Utilization of the load model at large scale for the control of multiple buildings requires robust and simpler optimization objectives.

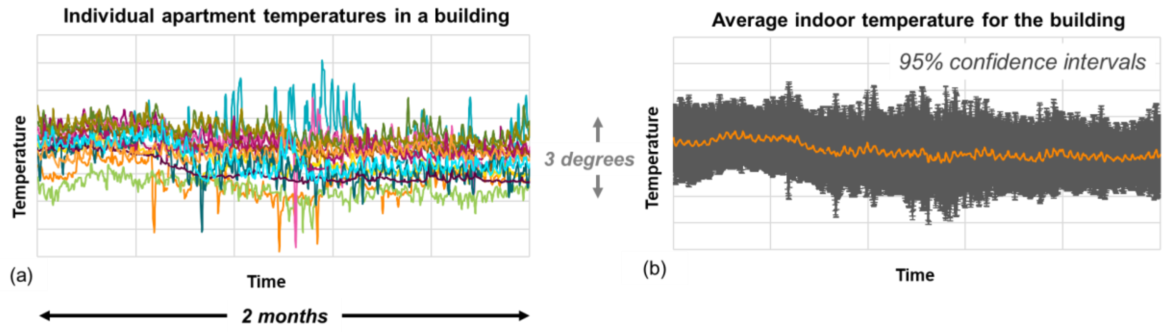

Figure 2: Distribution of indoor temperature for a two-month period in winter: (a) individual apartment temperatures; (b) average indoor temperature and associated uncertainty.

Figure 2(a) presents the distribution of individual apartment temperatures for a representative building in Sweden. The average indoor temperature is derived in Fig. 2(b). The associated levels of uncertainty within 95% confidence intervals are a metric of the social patterns and the building technology.

2.2. Model architecture

The model is trained in real time using standard data coming from the facility metering system. Past data from the apartments and heat exchanger are used for model training. Provided that a weather forecast is available, the model performs multi-step-ahead predictions for heat load and average indoor temperature within a designated prediction horizon. The architecture of the model is illustrated in Fig. 3.

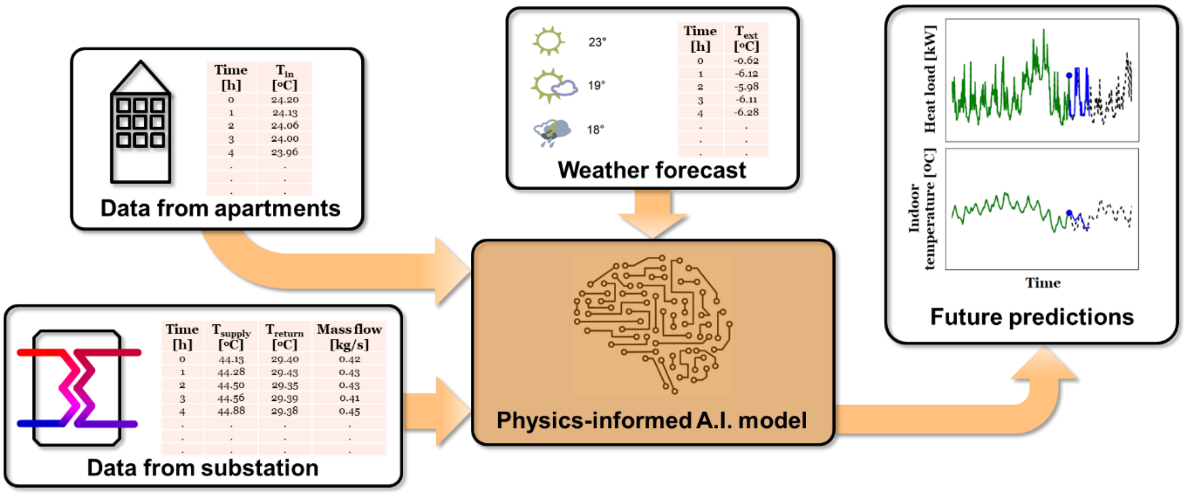

Figure 3: Architecture of heat load prediction model

Heat load is predicted through machine learning, whilst average indoor temperature is predicted through an adaptively-identified physics model (Vouros et al., 2022, Saletti et al., 2020, Saletti et al., 2021). The two models communicate with each other within a recursive numerical procedure.

2.3. Model calibration

Calibration of the model is conducted in terms of two parameters: (a) training window (past data), and (b) prediction horizon (future). A parametric analysis is set up employing two representative error metrics for the relative quantifications. Figure 4 presents the derivation of the error metrics.

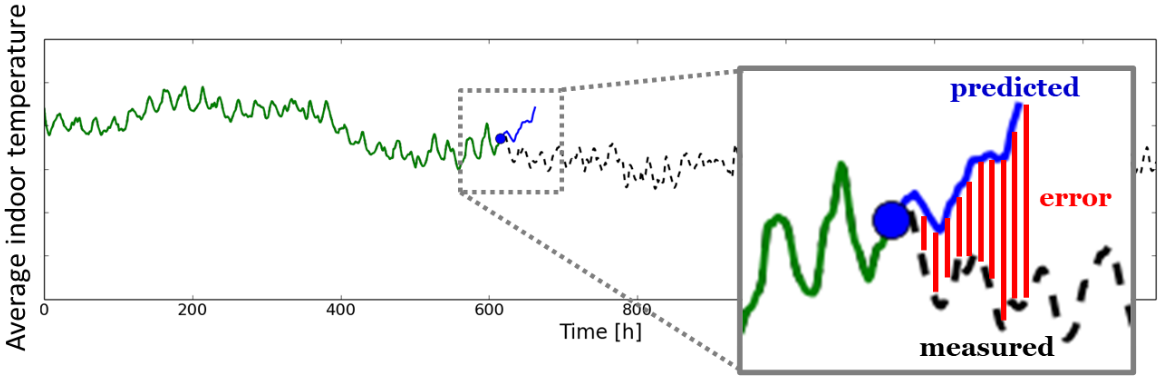

Figure 4: Distribution of error between multi-step ahead predictions and measured data

The adopter error metrics are the mean error and the maximum absolute error, both within the designated prediction horizon. The calibration campaign has yielded the following recommended set up and corresponding error quantification:

- Average indoor temperature can be predicted within up to 48h-ahead horizons with a mean absolute error of up to 0.5K and a maximum error of 1K.
- Heat rate can be predicted within up to 48h-ahead horizons with a mean absolute error of up to 10% and a maximum error of up to 30%.

Shorter prediction horizons may be used for networks with estimated delays in the order of a few hours. In that case, the modelling accuracy would be further improved.

The time window of past data required for training the model has an extent of 240h (i.e. 10 days). The model is adaptively updating the building thermal properties as well as the training of the machine learning model.

3. Verification

The calibrated model has been verified against measured data coming from three different buildings in Västerås, Sweden. Figure 5 illustrates three individual time instances for one selected building. The comparison is done in terms of heat load and average indoor temperature prediction within 48h-ahead horizons. The black dashed line represents measured data for this building. The green line represents the training data set with an extent of 240h. The blue line illustrates the predicted data, superimposed on the measured data. The gray uncertainty bars around average indoor temperature represent the 95% confidence intervals for this building. Overall, good agreement is observed between measured and predicted data. The purpose of this model is to be used within real time data-driven control optimization algorithms.

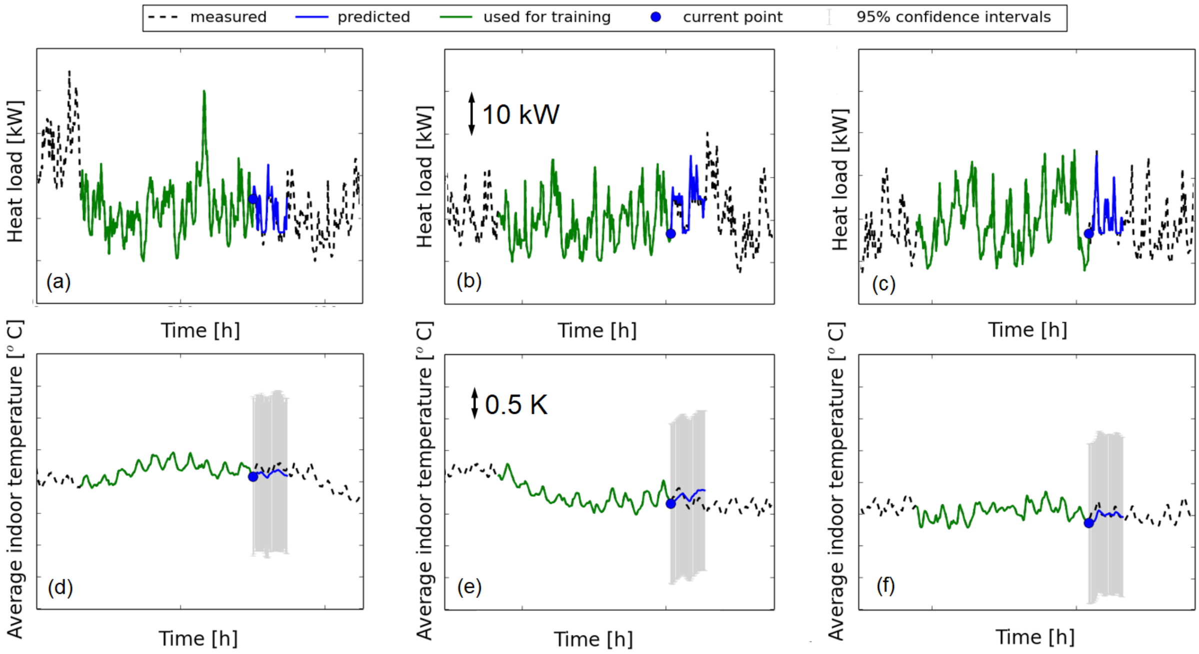

Figure 5: Multi-hour-ahead predictions at different time instances: heat load (a) t=305h, (b) t=610h, (c) t=1017h; average indoor temperature (d) t=305h, (e) t=610h, (f) t=1017h.

4. Conclusions

A physics-informed A.I. model has been developed for the prediction of heat load and average indoor temperature in district heating substations. The model has demonstrated adaptivity rendering it as a “plug-and-play” solution for real-time prediction without significant pre-tuning requirements. Error quantifications for the model have demonstrated acceptable accuracy and robustness. The model has been verified against measured data from three different buildings in Västerås, Sweden. Future use of the model involves integration into an optimization scheme for data-driven control.

List of references

Vouros S., Monghasemi N., Vadiee A., and Kyprianidis K.G., 2022. Real-time heat load prediction in district heating substations. *63rd International Conference of Scandinavian Simulation Society, SIMS 2022,* 20-21 September, Trondheim, Norway *(abstract accepted)*

Saletti, C., Gambarotta, A. and Morini, M., 2020. Development, analysis and application of a predictive controller to a small-scale district heating system. *Applied Thermal Engineering*, *165*, p.114558.

Saletti, C., Zimmerman, N., Morini, M., Kyprianidis, K. and Gambarotta, A., 2021. Enabling smart control by optimally managing the State of Charge of district heating networks. *Applied Energy*, *283*, p.116286.