Effect of measurement resolution on data-based models of thermodynamic behaviour of buildings

Thea Hauge Broholt[a], Louise Rævdal Lund Christensen[a], Steffen Petersen[a].

[a] Department of Civil and Architectural Engineering, Aarhus University, Denmark, thb@cae.au.dk.

Abstract. Multiple studies have investigated and shown a theoretical potential in utilising Model Predictive Control (MPC) of residential heating systems to lower CO_2-emissions. However, there are several practical issues in realising this potential. This paper reports on a simulation-based study focused on two of these issues both related to the data-based identification of a black-box state-space model for MPC. First, it is investigated how the measurement resolution of the heating energy consumption affects the precision of the model used for MPC. Second, the resolution analysis is combined with an investigation on whether it is possible to obtain appropriate models using data generated from excitation signals that in theory do not lead to occupant discomfort. The performance of the models was evaluated by combining different resolutions of data with different types of excitation signals. The results show that a Pseudo-Random Binary Sequence signal within a temperature span from 20 to 24 °C, and a time and data resolution of one hour and 0.1 kWh, respectively, of the heat consumption is expedient to ensure black-box models sufficient for MPC purposes.

Keywords. Black-box model, Data resolution, Model Predictive Control, Space heating.
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1. Introduction

The CO_2-emissions from energy use for heating in buildings has a large impact on reaching EU climate goals of being climate neutral by 2050 [1]; in 2019, 63.6 % of energy consumption in European households went to space heating [2]. In Denmark, and many other European countries, the heat supply is district heating. Therefore, district heating plays a large role in lowering the total energy consumption.

Multiple simulation studies show that the CO_2-emission from heating of buildings can be lowered through Model Predictive Control (MPC) of space heating systems. Knudsen and Petersen [3], compare a regular PID controller to an MPC, and find that MPC using forecast of CO_2-emissions as control signal lead to relatively large CO_2-reductions. A similar outcome is reported by Pedersen, Hedegaard and Petersen [4] who demonstrate that the CO_2-reducing effect of a similar MPC scheme on an apartment building is enhanced by energy retrofits. Avci et al. [5] compare MPC to a regular thermostat using both simulations and field tests and find that MPC lead to 5 % and 8 % energy reduction compared to the thermostat using fixed or variable temperature set points, respectively. Prívara et al. [6] implement an MPC in a real university building and obtain energy savings of 17-24 % compared to the original control system. Cigler et al. [7] use both simulation and a field test where they reach energy savings of 15 % and 28 % compared to the original well-tuned control strategy. All these studies show a significant potential in MPC for lowering CO_2-emissions from space heating.

An important aspect of MPC for space heating is to obtain a thermodynamic model of the thermal zone to be heated. This model can be obtained in different ways but is typically involving a calibration process using heating data from the thermal zone. The resolution of this data varies across studies. Knudsen and Petersen [3] and Pedersen, Hedegaard and Petersen [4] all use hourly time resolution of the heat load for their MPC, Avci et al. [5] use a sampling time of 15 minutes, and Cigler et al. [7] use a sampling interval as low as five minutes. Yu et al. [8] evaluates sampling times between 2.5 minutes and one hour. In most Danish households, the available heat consumption data is truncated kWh on an hourly basis as described in Kristensen and Petersen [9]. An example of truncation is as follows. If the heat consumption of hour 1 is 1.4 kWh, 1 kWh will be registered for hour 1, and 0.4 kWh will be added to the next hour (hour 2). Consumption in hour 2 is 5.8 kWh but as 0.4 was transferred from hour 1, a consumption of 6 kWh will be registered for hour 2, and 0.2 kWh will be added the next hour (hour 3), and so on. The question is whether this form of readily available data is useful for generating a model for MPC – let alone operate the heating system with MPC.

The purpose of this study is therefore to investigate whether this truncated data is sufficient to create high performing models. Literature typically indicate that a high model accuracy is a model fit between 80 % and 100 % [4,5,10], to name a few. However, for MPC purposes a model fit of approximately 70 % has been shown to be enough [11,12]. The investigation is performed by comparing the model performance from input with truncated data to input of finer resolution data. The study will then determine which resolution is needed to create models with sufficient accuracy for MPC purposes.

2. Method

The following sections briefly describe the EnergyPlus [13] model of the case building (section 2.1), the black-box model structure (section 2.2), the different excitation signals used for generating data for system identification (section 2.3), and heat consumption datasets with different precision and resolution (section 2.4).

2.1 Case building

The case building was a single-family residential building of 81 m². Fig. 1 shows a floorplan and an illustration of the building. A detailed description on the building construction is found in [14] (table 1). Three walls were exposed to the outdoors while the east wall was adiabatic. For the sake of simplicity, the building was modelled as one thermal zone, where internal walls were modelled as a heat capacity with the EnergyPlus class *InternalMass*. Windows and the living room door were modelled with a U-value of 0.74 W/(m²K) and a solar heat gain coefficient of 0.5 corresponding to a 3-layer low-E coated glazing, while the entrance door was modelled as non-transparent with a U-value of 0.67 W/(m²K).

Fig. 1 – Case building. Top: floorplan. Bottom: building illustration.

The building was natural ventilated with a design ventilation rate of 0.21 l/s per m², and a design infiltration rate of 0.09 l/s per m², i.e. a total rate of 0.3 l/s per m² in accordance with the Danish building regulation [15]. The actual ventilation rates were calculated by the EnergyPlus *BLAST* algorithm [16] leading to a ventilation rate that varies with wind-speed and indoor/outdoor temperature difference. The heating system was managed with a PI-controller, with a proportional band of 2 °C and an integral time of 600 seconds. The anti-windup technique *conditional integration (clamping)* was modelled for the integration part. This was modelled with EnergyPlus *EnergyManagerSystem:Program*. The ground temperature was modelled using default settings of the EnergyPlus class *Foundation:Kiva*, with exposed foundation perimeter set to the outer circumference of the case building.

Weather data for the simulation was obtained from [17], a service providing EnergyPlus weather files for user-defined locations in Denmark. Data from 2018 for a city near Aarhus (longitude: 10.0, latitude 56.06) was used.

2.2 Building model

The model used for MPC purposes was assumed to be a black-box model formulated as the linear state space model given in equation (1) and (2). This formulation is similar to the one in Knudsen and Petersen [10].

$$x[k+1] = \boldsymbol{A}x[k] + \boldsymbol{B}u[k] + \boldsymbol{K}e[k] \quad (1)$$
$$y[k] = \boldsymbol{C}x[k] + e[k] \quad (2)$$

where k is time step, $x[k] \in \mathbb{R}^n$ is system state, $y[k] \in \mathbb{R}^p$ is output (indoor air temperature [°C]), $u[k] \in \mathbb{R}^m$ is input (outdoor temperature [°C], global horizontal solar irradiation [W/m²] and heat from building heating system [W]) and $e[k] \in \mathbb{R}^p$ is output prediction error. $\boldsymbol{A} \in \mathbb{R}^{n\times n}$ is state matrix, $\boldsymbol{B} \in \mathbb{R}^{n\times m}$ is input matrix, $\boldsymbol{K} \in \mathbb{R}^{n\times p}$ is Kalman gain matrix, $\boldsymbol{C} \in \mathbb{R}^{p\times n}$ is output matrix.

The matrices ***A, B, C*** and ***K*** were initially estimated with the MATLAB method *N4SID* and afterwards refined with prediction error minimization (*PEM*). If *PEM* failed to create a model, the ***K***-matrix from *N4SID* was replaced by a zero-matrix. The settings for *N4SID* and *PEM* are given in Tab. 1 and Tab. 2, respectively. The settings were chosen because they provide the best accuracy of the model. Default settings were used when nothing else was given.

Tab. 1 – Chosen settings for *N4SID.*

Setting	Choice
Form	Companion
Model order	2
Time step (k)	One hour
Weight	CVA
Focus	Simulation
Horizon	Auto

Tab. 2 – Chosen settings for *PEM.*

Setting	Choice
Initial state	Estimate
Search method	Lm
Max iterations	500

The model was calibrated and validated through winter and transitional seasons (September to May). The calibration and validation period depend on the excitation signals described in the following section.

2.3 Excitation signals

When training the models for MPC, most studies have used the excitation signal Pseudo Random Binary Sequence (PRBS) signal, which one would expect to lead to discomfort for the occupants due to the highly varying heat load from the heating system. Examples of studies using such a signal are [3,4,18]. A few studies such as [8,14,19] compare PRBS signals to other types of signals. Broholt et al. [14] compare the model performance of models calibrated with a PRBS signal to models calibrated with a night-boosting signal. They find the performance of models calibrated with a PRBS signal is only marginally better than models calibrated with a night-boosting signal. Yu et al. [8] evaluate model performance of models trained with a night set-back signal and validated with a PRBS signal. They conclude that the night set-back signal is a good excitation signal. Knudsen et al. [19] compare the performance of an MPC based on a PRBS signal with an MPC based on an MPC signal. They find no significant difference in the performances.

The effect of excitation on the model accuracy was tested in this study by evaluating two types of excitation signals: The typically used PRBS signal, and a Night Boost (NB) signal like a signal usually observed in previously mentioned MPC studies. Two types of PRBS signals were tested:

1) lower and upper bound of 20 °C and 24 °C, respectively (see example in Fig. 2).
2) bounds between 21 °C and 23 °C.

There are different ways to design a PRBS signal to excite the heating system in buildings; Yu et al. [8] follow the guidelines of IEA EBC Annex 58 [21] that proposes to combine two different PRBS signals to identify both short and long time constants in a building using a short (e.g. 20 min.) and a long (e.g. 20 hour) period (T). Hedegaard et al. [20] also ensures a signal that identify the short and long time constants in the building. In this study, T is set to one hour. The goal is to train models for MPC that adjust heating setpoint on hourly basis, why a control signal with a T below one hour is not relevant. Models were both calibrated and validated with data where the heating system was excited with a PRBS signal. The calibration period with PRBS signal was the first 382 hours (15.9 days) each month (September-May), equal to a combination of two full-length PRBS signals of seventh and eighth order. The validation period was the last 255 hours (10.6 days) of each month, equal to a full length PRBS signal of eighth order.

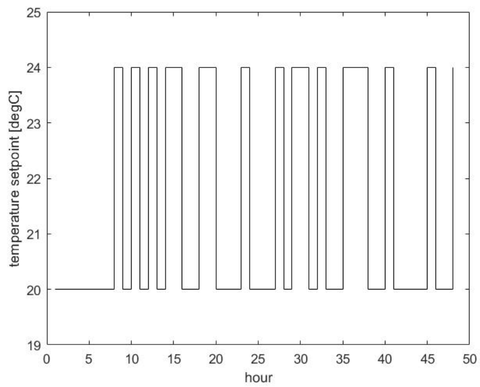

Fig. 2 – Example of the PRBS signal (first 48 hours of the seventh order signal).

Four different types of NB signals were constructed:

1) Boosting to 24 °C from 3 a.m. to 5 a.m. (see example in Fig. 3)
2) Boosting to 23 °C from 3 a.m. to 5 a.m.
3) Boosting to 24 °C from 1 a.m. to 5 a.m.
4) Boosting to 23 °C from 1 a.m. to 5 a.m.

For all four signals, the temperature set point was 22 °C outside the boosting period. The calibration period with NB signals was the first 16 days each month, and the validation period was the last 11 days each month. The same NB signal was used in the calibration and validation period. Furthermore, the models calibrated with a NB signal was also validated with a PRBS signal, as the PRBS signal is considered a more thorough test of calibrated models' capabilities.

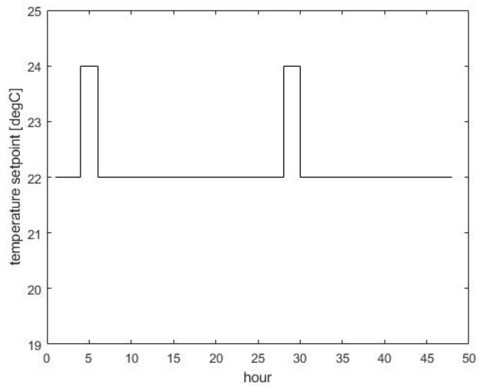

Fig. 3 – 48 hours of a NB signal.

2.4 Heat load data

We tested six different datasets of truncated heat consumption [kWh] to evaluate the impact on model performance:

1) 15-minute truncation for every 0.1 kWh (benchmark).
2) 15-minute truncation for every kWh.
3) 30-minute truncation for every 0.1 kWh.
4) 30-minut truncation for every kWh.
5) 1-hour truncation for every 0.1 kWh.
6) 1-hour truncation for every kWh (typical resolution in Danish district heat meters).

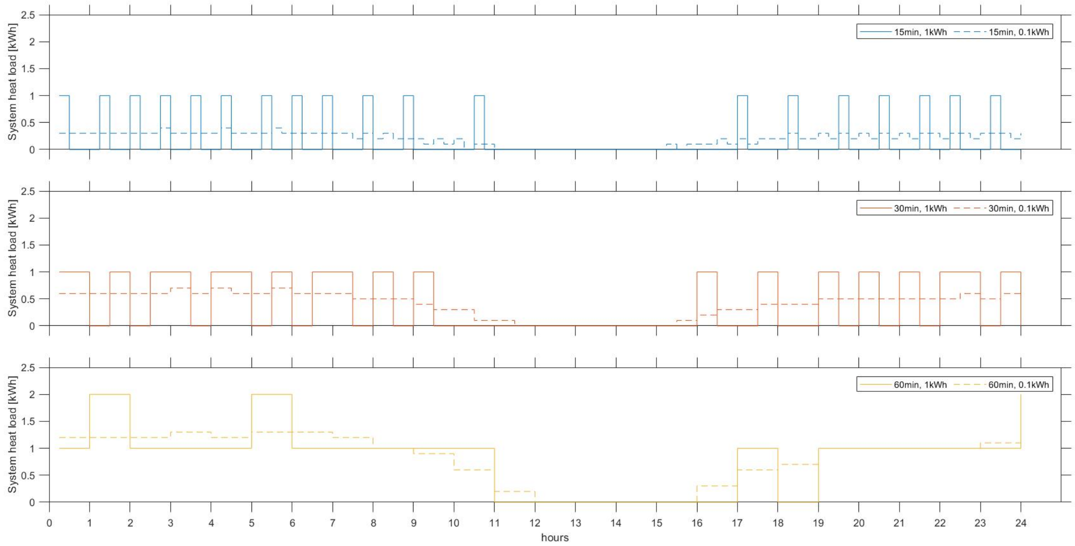

Fig. 4 – Example of the effect of truncation of the six evaluated datasets.

Fig. 4 illustrates how the six different precisions and resolutions varies using simulated one-minute consumption data from the case building on the last day of March. Temperature set point was kept constant at 22 °C. The datasets were created from the one-minute consumptions by summing all values within the given timestep and thereafter truncating the data, to recreate what the typical Danish heat meters would deliver.

3. Results

This section evaluates the performance of the black-box model described in section 2.2 when calibrating with a PRBS signal (see section 3.1) and with a NB signal (see section 3.2). The model performance is given by its ability to predict the indoor temperature 24 hours ahead in accordance with what would be appropriate for an MPC control. The model accuracy is described with the Root Mean Square Error (RMSE) [°C] and the Normalized Root Mean Square Error (NRMSE) [%]. The tables in this section show results from the six datasets described in section 2.4, when the models are calibrated and validated within the same month.

3.1 PRBS signals

Tab. 3 and Tab. 4 show the results for models calibrated and validated with a PRBS signal between 20 °C and 24 °C, and between 21 °C and 23 °C, respectively.

Tab. 3 – RMSE [°C] / NRMSE [%] with PRBS signal between 20 °C and 24 °C. Green: NRMSE > 70 %, yellow: NRMSE 70-50 %, and red: NRMSE < 50 %.

		Jan	Feb	Mar	Apr	May	Sep	Oct	Nov	Dec
1 hour	1 kWh	0.8 / 57	1.0 / 49	0.6 / 65	1.3 / 11	0.4 / 77	0.7 / 41	1.3 / -2	2.0 / 1	0.6 / 69
	0.1 kWh	0.4 / 79	0.7 / 64	0.4 / 80	0.9 / 40	0.3 / 84	0.6 / 48	0.6 / 56	0.8 / 60	0.2 / 89
30 min.	1 kWh	1.0 / 47	1.6 / 13	0.9 / 49	1.0 / 30	0.3 / 80	0.8 / 29	0.9 / 29	1.2 / 36	0.9 / 55
	0.1 kWh	0.5 / 75	0.7 / 65	0.4 / 79	0.7 / 49	0.3 / 84	0.6 / 49	0.6 / 53	1.0 / 50	0.3 / 85
15 min.	1 kWh	1.0 / 43	1.6 / 13	1.1 / 37	1.1 / 18	0.3 / 79	0.8 / 28	1.4 / -16	1.1 / 42	1.0 / 46
	0.1 kWh	0.7 / 61	0.6 / 64	0.4 / 78	0.6 / 57	0.3 / 81	0.7 / 38	0.6 / 54	0.9 / 51	0.3 / 83

Tab. 4 – RMSE [°C] / NRMSE [%] with PRBS signal between 21 °C and 23 °C Green: NRMSE > 70 %, yellow: NRMSE 70-50 %, and red: NRMSE < 50 %.

		Jan	Feb	Mar	Apr	May	Sep	Oct	Nov	Dec
1 hour	1 kWh	0.7 / 28	0.8 / 22	0.7 / 34	1.0 / 28	0.4 / 77	0.6 / 45	1.2 / -20	0.8 / 16	0.6 / 42
	0.1 kWh	0.3 / 69	0.5 / 47	0.3 / 68	0.7 / 50	0.3 / 84	0.6 / 46	0.5 / 48	0.5 / 50	0.2 / 84
30 min.	1 kWh	0.7 / 26	1.0 / -3	0.9 / 8	0.9 / 31	0.4 / 76	0.7 / 34	1.3 / -31	0.7 / 28	0.9 / 6
	0.1 kWh	0.3 / 67	0.5 / 49	0.3 / 66	0.5 / 61	0.3 / 84	0.6 / 43	0.6 / 45	0.5 / 52	0.2 / 80
15 min.	1 kWh	0.8 / 22	1.1 / -18	0.9 / 12	1.1 / 21	0.5 / 72	0.7 / 32	1.3 / -33	1.1 / -12	0.8 / 22
	0.1 kWh	0.6 / 43	0.5 / 47	0.4 / 64	0.5 / 61	0.3 / 84	0.7 / 30	0.6 / 44	0.6 / 42	0.2 / 76

Tab. 3 and Tab. 4 both show that the model accuracy is higher with truncation to 0.1 kWh compared to truncation to 1 kWh and nothing is gained from choosing a finer timestep than one hour. Furthermore, it is seen that a little higher accuracy is reached using a higher temperature fluctuation (Tab. 3) compared to the small temperature fluctuation (Tab. 4) when comparing NRMSE, while the RMSE is almost the same. The NRMSE indicate that the model accuracy is only appropriate for MPC (>70 %) in maximum four of the nine evaluated months.

3.2 Night boost signals

Tab. 5 and Tab. 6 show the results when then model is calibrated with a NB signal, boosting to 24 °C for two and four hours, respectively, and validated with a PRBS signal between 20 °C and 24 °C.

Tab. 5 – RMSE [°C] / NRMSE [%] when calibrating with NB signal; 2 hour boost to 24 °C and validating with PRBS signal between 20 °C and 24 °C . Green: NRMSE > 70 %, yellow: NRMSE 70-50 %, and red: NRMSE < 50 %.

		Jan	Feb	Mar	Apr	May	Sep	Oct	Nov	Dec
1 hour	1 kWh	1.2 / 35	1.4 / 27	1.3 / 31	1.1 / 26	0.3 / 81	0.9 / 19	0.8 / 40	1.4 / 31	3.0 / -54
	0.1 kWh	0.6 / 66	0.7 / 63	0.7 / 61	0.5 / 64	0.3 / 83	0.8 / 31	0.5 / 59	0.5 / 76	0.5 / 76
30 min.	1 kWh	1.8 / 2	1.5 / 17	2.0 / -12	1.6 / -15	0.3 / 82	1.0 / 11	1.0 / 20	1.7 / 10	2.4 / -28
	0.1 kWh	0.8 / 58	0.7 / 62	0.7 / 58	0.5 / 64	0.3 / 81	0.7 / 37	0.6 / 57	0.5 / 73	0.5 / 72
15 min.	1 kWh	1.4 / 21	1.5 / 15	1.4 / 17	1.2 / 15	0.3 / 81	1.0 / 11	1.0 / 21	2.0 / -7	1.5 / 17
	0.1 kWh	0.8 / 58	0.7 / 60	0.9 / 49	0.5 / 63	0.3 / 84	0.8 / 28	0.6 / 55	0.7 / 65	0.5 / 70

Tab. 6 – RMSE [°C] / NRMSE [%] when calibrating with NB signal; 4 hour boost to 24 °C and validating with PRBS signal between 20 °C and 24 °C . Green: NRMSE > 70 %, yellow: NRMSE 70-50 %, and red: NRMSE < 50 %.

		Jan	Feb	Mar	Apr	May	Sep	Oct	Nov	Dec
1 hour	1 kWh	1.1 / 40	1.5 / 20	1.3 / 28	1.1 / 22	0.3 / 80	0.8 / 31	0.8 / 41	1.9 / 2	1.1 / 42
	0.1 kWh	0.9 / 53	0.7 / 61	0.9 / 49	0.5 / 63	0.3 / 83	0.7 / 40	0.5 / 60	0.5 / 75	0.5 / 75
30 min.	1 kWh	1.6 / 14	1.6 / 14	1.5 / 14	1.1 / 18	0.4 / 79	0.9 / 23	1.0 / 21	2.8 / -43	1.4 / 25
	0.1 kWh	0.8 / 55	0.7 / 62	0.9 / 51	0.5 / 62	0.3 / 84	0.6 / 42	0.6 / 55	0.6 / 71	0.6 / 67
15 min.	1 kWh	1.4 / 24	1.5 / 17	1.4 / 21	1.3 / 9	0.3 / 81	0.8 / 29	1.0 / 17	3.3 / -74	1.5 / 18
	0.1 kWh	0.8 / 54	0.7 / 59	0.9 / 50	0.5 / 61	0.3 / 82	0.7 / 32	0.6 / 53	0.6 / 67	0.6 / 66

The same tendency as when calibrating with the PRBS signals can be observed: the models perform better with truncation to 0.1 kWh compared to 1 kWh while nothing is gained from choosing a finer timestep than one hour. The results of a smaller temperature fluctuation are not shown in a table, but the tendencies are the same: the mean and standard deviation of the RMSE/NRMSE across the nine months, when boosting for 2 hours to 23 °C and validating with a PRBS signal between 21 °C and 23 °C, is 0.8 ± 0.2 °C/ 27 ± 23 %, 0.8 ± 0.2 °C/ 24 ± 24 %, and 0.9 ± 0.3 °C/ 12 ± 34 % when truncating to 1 kWh with timestep 1 hour, 30 min., and 15 min., respectively. While the mean and standard deviation of the RMSE/NRMSE, when truncating to 0.1 kWh, is 0.5 ± 0.3 °C/ 52 ± 23 %, 0.5 ± 0.3 °C/ 50 ± 20 %, and 0.7 ± 0.4 °C/ 28 ± 41 %, respectively.

A comparison of the results in Tab. 5 to the results in Tab. 6 show that little to nothing is gained in relation to model accuracy from boosting the temperature for four hours (Tab. 6) instead of two hours (Tab. 5). Only in September (with a timestep of one hour and truncation to 0.1 kWh) do we see a little higher NRMSE.

Tab. 7 and Tab. 8 show the results for models calibrated and validated with a NB signal boosting to 24 °C for two and four hours, respectively. These results also show a tendency of the model accuracy being higher when truncating to 0.1 kWh compared to truncation to 1 kWh. The model accuracy does not increase when using a finer timestep than one hour. The results with a boost to 23 °C show the same tendencies as well; the mean and standard deviation of the RMSE/NRMSE across the nine months, when boosting for two hours, is 0.5 ± 0.2 °C/ 0 ± 54 %, 0.5 ± 0.2 °C/ -7 ±62 %, and 0.5 ± 0.4 °C/ -3 ± 93 when truncating to 1 kWh with timestep 1 hour, 30 min., and 15 min., respectively. The mean and standard deviation of the RMSE/NRMSE, when truncating to 0.1 kWh, is 0.5 ± 0.3 °C/ 9 ± 50 %, 0.4 ± 0.2 °C/23 ± 38 %, and 0.5 ± 0.3 °C/-9 ± 100 %, respectively.

A comparison of results from Tab. 7 and Tab. 8 to results from Tab. 3 and Tab. 4 show that models calibrated with a simple NB signal does not perform as good as models calibrated with the more fluctuating PRBS signal, not even when the validation signal is simple too.

Tab. 7 – RMSE [°C] / NRMSE [%] with NB signal; 2 hour boost to 24 °C. Green: NRMSE > 70 %, yellow: NRMSE 70-50 %, and red: NRMSE < 50 %.

		Jan	Feb	Mar	Apr	May	Sep	Oct	Nov	Dec
1 hour	1 kWh	0.4 / 23	0.8 / -42	0.6 / -3	0.9 / 33	0.3 / 81	0.6 / 40	0.7 / 12	1.0 / -76	0.6 / -9
	0.1 kWh	0.3 / 43	0.4 / 24	0.3 / 49	0.4 / 69	0.3 / 84	0.5 / 51	0.5 / 35	0.2 / 64	0.1 / 79
30 min.	1 kWh	0.7 / -21	0.8 / -37	0.7 / -8	1.2 / 9	0.3 / 82	0.7 / 30	1.2 / -54	1.2 / -111	0.5 / 1
	0.1 kWh	0.4 / 27	0.4 / 35	0.3 / 46	0.4 / 68	0.3 / 81	0.4 / 58	0.5 / 37	0.2 / 67	0.1 / 75
15 min.	1 kWh	0.5 / 12	0.7 / -26	0.6 / 7	1.0 / 24	0.3 / 81	0.8 / 29	1.1 / -40	1.4 / -152	0.5 / 2
	0.1 kWh	0.4 / 28	0.4 / 33	0.4 / 32	0.4 / 68	0.3 / 83	0.5 / 48	0.5 / 35	0.2 / 58	0.2 / 68

Tab. 8 – RMSE [°C] / NRMSE [%] with NB signal; 4 hour boost to 24 °C. Green: NRMSE > 70 %, yellow: NRMSE 70-50 %, and red: NRMSE < 50 %.

		Jan	Feb	Mar	Apr	May	Sep	Oct	Nov	Dec
1 hour	1 kWh	0.5 / 35	1.0 / -38	0.9 / -11	1.0 / 29	0.3 / 81	0.6 / 42	0.7 / 25	2.0 / -167	0.5 / 39
	0.1 kWh	0.5 / 36	0.5 / 33	0.5 / 43	0.5 / 67	0.3 / 83	0.5 / 53	0.5 / 46	0.2 / 69	0.1 / 83
30 min.	1 kWh	0.7 / 3	1.0 / -33	1.1 / -39	1.0 / 27	0.3 / 80	0.8 / 33	1.2 / -27	2.6 / -246	0.6 / 23
	0.1 kWh	0.4 / 40	0.4 / 46	0.4 / 48	0.5 / 67	0.3 / 84	0.4 / 60	0.5 / 45	0.2 / 73	0.1 / 80
15 min.	1 kWh	0.6 / 24	0.7 / 0	0.6 / 19	1.1 / 18	0.3 / 82	0.7 / 38	1.1 / -23	2.9 / -287	0.7 / 9
	0.1 kWh	0.4 / 41	0.4 / 44	0.4 / 45	0.5 / 66	0.3 / 82	0.5 / 51	0.5 / 43	0.2 / 71	0.2 / 77

4. Discussion

The results of 24-hours ahead predictions indicate that model accuracy increases significantly when heat load is truncated to 0.1 kWh instead of 1 kWh. This is also the case for 1-hour ahead prediction: Models calibrated and validated with a PRBS signal between 20 °C and 24 °C and truncation to 1 kWh led to a mean and standard deviation across the nine months of 35 ± 39 % while truncation to 0.1 kWh led to a mean and standard deviation across the nine months of 83 ± 9 %. The latter accuracy corresponds to other studies using 1-step ahead predictions, e.g. [4,5,10], where the NRMSE are between 80 % and 100 %. However, in [10], they have high performing models for one-step ahead as well as 24-step ahead predictions. This may be due to their choice of inputs. For example, they use the solar radiation on the window surface which highly correlates with the room temperature. In this study we chose the global solar radiation as this is easily measured compared to the solar radiation on the window surfaces.

In general, the models perform much better in some months (the heating season November-March) compared to other months (e.g. April and September). This could indicate that the models are not robust to changes in the input data; in the heating season the outdoor conditions do not change significantly. In May, the heat load is zero most of the month which can explain why the truncation does not have an effect here. In April and September, the outdoor conditions change from the calibration period to the validation period which is why the model accuracy may be reduced in these months. However, the RMSE is below 1 °C in most cases.

5. Conclusion

The purpose of this paper was twofold. First, it was to evaluate how the data resolution on the heating energy consumption affected the ability of a black-box model to predict the indoor temperature 24 hours ahead. The model accuracy is of high importance when performing MPC. The results showed that the resolution of the data itself had a larger effect than the time resolution of the data. Meaning that data changed from the commonly used resolution of 1 kWh to a resolution of 0.1 kWh led to a higher increase in NRMSE and reduction in RMSE compared to a change in timestep (comparing one hour, 30 min., and 15 min. timesteps). Therefore, a one-hour timestep with a 0.1 kWh data resolution seems appropriate for MPC. Furthermore, this means that the typically used data measurements in Denmark (one hour and 1 kWh resolution) does not have to be changed much for an MPC to be possible in Danish households.

The second purpose of the paper was to investigate whether sufficient black-box models could be obtained from data generated with an excitation signal which in theory does not lead to occupant discomfort (NB signal). This was done by comparing the performance of black-box models calibrated with an NB signal to black-box models calibrated with the commonly used and more fluctuating PRBS signal. The results showed that the model accuracy, in terms of NRMSE, was highest when calibrating and validating with a PRBS signal with a temperature span between 20 °C and 24 °C. However, the narrow temperature span (21-23 °C) gave similar results, in terms of RMSE. When calibrating with an NB signal, the model accuracy falls in terms of NRMSE, while the RMSE is kept below 1 °C for all cases with truncation to 0.1 kWh and one hour time step. Further investigation of simple excitation signals, which theoretically lead to less discomfort compared to the highly fluctuating PRBS signal, could be a potential next step.

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7. Data access

The datasets generated during and analysed during the current study are not publicly available due to practical reasons but will be available from contacting the authors.

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