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Thermal building modelling using Gaussian processes

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ABSTRACT

This paper analyzes the suitability of Gaussian processes for thermal building modelling by comparing the day-ahead prediction error of the internal air temperature with a grey-box model. The reference building is a single-zone office with a hydronic heating system, modelled in TRNSYS and simulated during the winter and spring periods. Using the output data of the reference building, the parameters of a Gaussian process and of a physics-based grey-box model are identified, with training periods ranging from three days to six weeks. After three weeks of training, the Gaussian processes achieve 27% lower prediction errors during occupied times compared to the grey-box model. During unoccupied times, however, the Gaussian processes perform consistently worse than the grey-box model. This is due to their large generalization error, especially when faced with untrained ambient temperature values. To reduce the impact of changing weather conditions, adaptive training is applied to the Gaussian processes. When re-training the models every 24 h, the prediction error is reduced over 21% during unoccupied times and over 10% during occupied times compared to the non-adaptive training case. These results show that the proposed Gaussian process model can correctly describe a building's thermal dynamics. However, in its current form the model is limited to applications where the prediction during occupied times is more relevant.

1. Introduction

In recent years there has been an increased research interest in model predictive control (MPC) for buildings [1], which calculates the optimal control inputs for the heating, ventilation and air conditioning (HVAC) system based on some optimization criterion, such as energy consumption. Because MPC requires models of the building and of its subsystems, it is the objective of this paper to evaluate the suitability of Gaussian processes (GPs) [2], a machine learning method, for this purpose. The suitability of the model is evaluated based on the day-ahead prediction error of the building's internal air temperature and on its generalization error, i.e. the error caused by testing the model with untrained input data.

In the literature there are diverse examples of the use of GPs for building applications, although most focus on energy consumption rather than thermal dynamics. Ghosh et al. [3] propose a 'latent force' model aimed at correctly describing the internal air temperature in a residential building. The model consists of a combination between a simplified grey-box model and a stochastic term modelled with a GP. The GP term compensates the systematic errors of the grey-box model, improving the predictions. Heo and Zavala [4] develop GP models to calculate energy savings and uncertainty levels in measurement and verification practices for retrofitted buildings. They compare the GPs to a linear regression method, showing that the GPs are able to represent the nonlinear behaviour of the system. Manfren et al. [5] implemented a GP model to estimate monthly electricity and natural gas consumption in a retrofitted building, obtaining similar results compared to a detailed model. Yan and Malkawi [6] use GPs to predict cooling and heating consumption and compare it to a neural network model, showing that their prediction accuracy is similar. To the best of the authors' knowledge, there are no published studies that analyze the day-ahead temperature prediction capabilities of Gaussian process models.

This paper advances the state of the art by developing and evaluating a GP regression model to predict the day-ahead zone temperature in a building. The GP is subject to different investigations, which include the selection of the mean function, the covariance function and the input set, the variation of the training period, an evaluation of the generalization error and adaptive training. The results obtained with the GP are compared to a grey-box model based on simplified thermal resistance-capacitance circuits, a modelling method often used in the literature [7–11].

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Nomenclature

Symbol

c_{H_2O}	specific heat capacity of water, J/(kg K)
$c_{p,air}$	specific heat capacity of air, J/(kg K)
C_{zone}	zone heat capacity, J/K
C_{wall}	wall heat capacity, J/K
C_{rad}	radiator heat capacity, J/K
DoW	day of week, –
GB	grey-box model, –
GP	Gaussian process model, –
h_{air}	enthalpy of air, J/(kg K)
HoD	hour of day, –
HSch	heating schedule, –
HVAC	heating, ventilation and air-conditioning, –
I	identity matrix, –
$k(\cdot)$	covariance function, –
$k_{SE}(\cdot)$	squared exponential covariance function, –
$k_{Matérn}(\cdot)$	Matérn exponential covariance function, –
K	covariance matrix, –
ℓ	characteristic length-scale, –
$m(\cdot)$	mean function, –
$\dot{m}$	heating medium mass flow, kg/s
$\dot{m}_{air}$	mass flow of the infiltrated air, kg/s
MPC	model predictive control, –
n	number of observations/measurements, –
n_{inf}	infiltration rate, h^{-1}
n_{rad}	radiator exponent, –
N_{occ}	number of occupants, –
$\dot{Q}_N$	radiator norm heating power, W
$\dot{Q}_{rad}$	heat flow rate between the heating medium and radiator, W
$\dot{Q}_{sol}$	solar gains, W
$\dot{Q}_{wall,amb}$	wall-ambient heat flow rate, W
$\dot{Q}_{zone,rad}$	zone-radiator heat flow rate, W
$\dot{Q}_{zone,wall}$	zone–wall heat flow rate, W
r	Euclidean length of $\mathbf{u} - \mathbf{u}'$, –
$R_{wall,amb}$	wall-ambient thermal resistance, W/K
$R_{zone,rad}$	zone-radiator thermal resistance, W/K
$R_{zone,wall}$	zone-wall thermal resistance, W/K
RMSE	root mean square error of the zone temperature prediction, K
$RMSE_{total}$	total RMSE, K
$RMSE_o$	RMSE during occupied times, K
$RMSE_{uo}$	RMSE during unoccupied times, K
u	input, –
$\mathbf{u}$	input vector, –
U	matrix with input vectors, –
V_{zone}	volume of the zone, m^3
y	output, –
$\mathbf{y}$	output vector, –
$\Delta\dot{H}_{air}$	net enthalpy rate due to air infiltration, W
$\Delta\vartheta_{lg,N}$	norm logarithmic temperature, K
ϑ_{amb}	ambient temperature, °C
ϑ_{wall}	wall temperature, °C
ϑ_{rad}	radiator temperature, °C
ϑ_{supply}	supply temperature of the heating medium, °C
$\boldsymbol{\mu}_{test}$	the GP's predicted mean value, –
ν	hyperparameter of the Matérn kernel, –
ρ_{air}	density of air, kg/m^3
σ_ϵ^2	variance of the noise in the measurements, –

Table 1
General characteristics of the reference building, heating system and occupancy data.

Characteristic	Value	Units
Number of zones	1	–
Floor area	800	m^2
Zone height	3.5	m
Window area	60	m^2
Glazed façade	14	%
Window orientation	South	–
Window *U*-value	1.4	$W/(m^2 K)$
Wall *U*-value	0.339	$W/(m^2 K)$
Ceiling *U*-value	0.233	$W/(m^2 K)$
Volumetric infiltration rate	0.2	n^{-1}
Temperature setpoint	23	°C
Radiator exponent	1.33	–
Radiator area	46.8	m^2
Cooling system	Not present	–
Occupied hours	7:00–19:00	–
Occupied days	Monday to Friday	–
Number of occupants	25	Persons
Gains per occupant	120	W
Office equipment gains	200	W/occ.
Lighting gains	5	W/m^2
Lighting schedule	7:00–9:00 and 16:00–19:00	–

2. Modelled building

The modelled building consists of an office located in Stuttgart, Germany. The building is well-insulated and has a south-facing window. Based on the building's characteristics (see Table 1) and using the DIN 12831 [12] and VDI 6030 [13] standards, a radiator-based heating system was designed. The reference building was modelled using TRNSYS 17 [14] with a 15-min time step, from where the data used for training the grey-box and the GP models is obtained. The controller, the grey-box model and the GP models were implemented in Matlab [15]. In order to control the TRNSYS building with a Matlab-based controller, the BCVTB co-simulation platform was used [16]. The weather data corresponds to the Meteonorm file for Stuttgart, which is included in TRNSYS 17.

The heating system operates on a predefined schedule, beginning at 4:00 am and is turned off at 19:00. The zone temperature control is done using thermostatic valves, which are modelled as a proportional-integral (PI) controller. By opening or closing the valves, the mass flow through the radiators is regulated. The other control input, the supply temperature of the heating medium, is defined with a lookup table that has a linear dependence on the ambient temperature, having a maximum value of 60 °C. The occupancy profile and the internal gains due to the occupants, office equipment and lighting are presented in Fig. 1. The lighting schedule is from 7:00 to 9:00 and 16:00 to 19:00.

3. Grey-box model

The grey-box model in this paper is based on physical principles but simplifies the mathematical system description by 'lumping' certain parameters. For example, instead of describing each wall in function of the dimensions and properties of the different layers that constitute it, it is represented by aggregated ('lumped') values describing the thermodynamic properties of the wall as a whole, such as the overall heat transfer coefficient and total heat capacity.

3.1. Model description

The structure of the grey-box model is analogous to electrical resistance-capacitance (RC) networks, the electrical resistance being replaced by the thermal resistance between thermal nodes (states) and the capacitance by the heat capacity of the nodes (see