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A hybrid approach to thermal building modelling using a combination of Gaussian processes and grey-box models

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ABSTRACT

This paper presents a hybrid building modelling method with a reduced modelling and calibration effort. The method combines a physics-based model, which describes the general behaviour of the system, with a machine learning algorithm trained to correct the physics-based model's systematic errors. To exemplify the method, a highly simplified grey-box model is used as the physics-based part and a Gaussian process as the machine learning part. It is shown that the hybrid model improves the temperature and energy predictions of the grey-box model while having a lower generalization error than the pure Gaussian process. Specifically, the hybrid approach achieved a day-ahead zone temperature prediction error ca. 0.1 K (RMSE) lower than the grey-box model. As for the energy prediction, the hybrid model obtained an error of 3% compared to 8% for the grey-box model. In comparison to the Gaussian process, the hybrid approach achieved better predictions in all cases. The improvements were especially high when the models were trained with small datasets: 0.7 K in the temperature prediction and 25 percentage points in the energy prediction.

1. Introduction

In Europe, buildings are responsible for ca. 40% of total energy consumption [1], making the building sector a prime target for energy efficiency measures. Mathematical modelling can contribute to more energy-efficient buildings by aiding in design [2], retrofit [3] and control applications [4], among others. However, the heterogeneous nature of the building stock makes the modelling of any individual building a challenging and expensive task. As a direct consequence of this, building modelling represents a bottleneck that avoids the widespread use of promising technologies, such as model predictive control [5–7].

With the motivation of reducing the effort required to develop building models, this paper presents a hybrid modelling method that combines physics-based models with machine learning techniques. The physics-based model is used to describe the general behaviour of the system while the machine learning part learns and corrects the physics-based model's systematic errors. It is expected that certain desirable characteristics of both modelling methods will be transferred to the hybrid model. Firstly, machine learning is attractive due to its low modelling effort: input-output relationships can be learned automatically from the training data [8]. Secondly, physics-based models have a relatively low generalization error, showing a robust behaviour even when trained with small datasets [9]. To exemplify the method, a highly simplified grey-box model is used as the physics-based part and a Gaussian process (GP) [10] as the machine learning part. The hypothesis is that the hybrid model will improve the grey-box model's predictions while having a lower generalization error than pure GP models. If the hypothesis holds, the modelling effort will have been reduced by greatly simplifying the grey-box model and the calibration effort will be lower by requiring less training data than the pure GP.

The use of GPs to *structurally* complement physics-based models is analyzed by Álvarez et al. [11], who refer to this combination as 'Latent Force Models' (LFMs).

To the best of the authors' knowledge, LFMs have only been applied to building simulation by Ghosh et al. [12]. In their paper, an LFM is used to predict the temperature in a building and is shown to obtain better results than three different grey-box models. However, their LFM model has certain disadvantages. Firstly, the GP is trained simultaneously with the grey-box model, causing the parameters of the latter to experience an undesirable [12] loss in their physical interpretability. Secondly, the GP model uses time as its only input. Good results are obtained when evaluating the LFM on the training data, but when testing on an independent dataset

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Nomenclature

Symbol	Description	Unit
c_{H_2O}	Specific heat capacity of water	J/(kg K)
C_{chc}	Chilled ceiling heat capacity	J/K
C_{rad}	Radiator heat capacity	J/K
C_{wall}	Wall heat capacity	J/K
C_{zone}	Zone heat capacity	J/K
DAEPE	Day ahead energy prediction error	–
E_{th}	Thermal energy consumption	J
GB	Grey-box model	–
GP	Gaussian process model	–
H	Hybrid model	–
HVAC	Heating, ventilation and air-conditioning	–
LFM	Latent Force Model	–
I	Identity matrix	–
$k(\cdot)$	Covariance function	–
$k_{Matérn}(\cdot)$	Matérn covariance function	–
K	Covariance matrix	–
ℓ	Characteristic length-scale	–
$m(\cdot)$	Mean function	–
$\dot{m}$	Heating medium mass flow	kg/s
m_{day}	Number of days in a year	–
n	Number of observations/measurements	–
P_{th}	Thermal power consumption	W
PI	Proportional-integral controller	–
$\dot{Q}_{CC}$	Heat removed from the ventilation air through the cooling coils	W
$\dot{Q}_{HC}$	Heat transferred to the ventilation air through the heating coils	W
$\dot{Q}_{int}$	Internal heat gains	W
$\dot{Q}_{chc}$	Heat flow rate between the cooling medium and the chilled ceilings	W
$\dot{Q}_{rad}$	Heat flow rate between the heating medium and the radiators	W
$\dot{Q}_{vent}$	Net heat flow supplied to the zone by the ventilation	W
$\dot{Q}_{zone,chc}$	Zone–chilled ceiling 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	K/W
$R_{zone,chc}$	Zone–chilled ceiling thermal resistance	K/W
$R_{zone,rad}$	Zone–radiator thermal resistance	K/W
$R_{zone,wall}$	Zone–wall thermal resistance	K/W
RMSE	Root mean square error of the zone temperature prediction	K
$\mathbf{u}$	Input vector	–
U	Matrix with input vectors	–
V_{zone}	Volume of the zone	m^3
y	Output	–
$\mathbf{y}$	Output vector	–
Δt	Time step	s
ε_r	Relative error	–
ϑ_{amb}	Ambient temperature	°C
ϑ_{chc}	Chilled ceiling temperature	°C
$\vartheta_{chc,s}$	Chilled ceiling supply temperature	°C
$\vartheta_{chc,r}$	Chilled ceiling return temperature	°C
ϑ_{rad}	Radiator temperature	°C
$\vartheta_{rad,s}$	Radiator supply temperature	°C
$\vartheta_{rad,r}$	Radiator return temperature	°C
$\vartheta_{vent,s}$	Supply temperature of the ventilation air	°C
ϑ_{wall}	Wall temperature	°C
ϑ_{zone}	Zone temperature	°C
$\boldsymbol{\mu}_{test}$	The GP's predicted mean value	–
ν	Hyperparameter of the Matérn kernel	–
σ	Standard deviation	–
σ_ϵ^2	Variance of the measurement noise	–

this forces the GP to extrapolate and default to its mean function. The present paper overcomes these disadvantages by training the hybrid model's parts separately and by extending the GP's input space.

To the best of the authors' knowledge, this paper advances the state of the art by being the first to apply GPs with explicit basis functions [10] to the prediction of air temperature and energy consumption in buildings. This method is conceptually similar to the LFM model in [12], inasmuch as physics-based and Gaussian process models are combined to form a hybrid model, but with the differences mentioned in the previous paragraph. Other contributions include comparing the energy and temperature predictions of the grey-box, GP and hybrid models, as well as evaluating the robustness of the hybrid and grey-box models when presented with incorrect input data.

Table 1
General system characteristics.

Building characteristics	Value	Units
Floor area	800	m^2
Zone height	3.5	m
Southern window area	60	m^2
Northern window area	60	m^2
Window U-Value	1.4	$W/(m^2\ K)$
Wall U-Value	0.339	$W/(m^2\ K)$
Ceiling U-Value	0.233	$W/(m^2\ K)$
Passive infiltration rate	0.2	h^{-1}
HVAC system		
Temperature setpoint	23	°C
Radiator exponent	1.33	–
Radiator area	36	m^2
Chilled ceiling area	302	m^2
Ventilation volume flow	3300	m^3/h
Shading irradiation limit	200	W/m^2
Shading transmittance	10	%
Occupancy and internal gains		
Occupied hours	7:00–19:00	–
Occupied days	Monday to Friday	–
Number of occupants	40	Persons
Gains per occupant	120	W
Office equipment gains	200	W/occ.
Lighting gains	5	W/m^2

2. Modelled building

The reference building consists of a single-zone office located in Stuttgart, Germany. The building has an east–west layout with windows on the southern and northern façades. External blinds are used to avoid direct solar radiation entering the zone. Radiators and chilled ceilings are responsible for the main heating and cooling in the building, while a ventilation system is installed to ensure a minimum air exchange rate [13]. The building, radiators and chilled ceilings were modelled using TRNSYS 17 [14] and the rest of the HVAC system (Fig. 1) was modelled in Matlab [15]. The zone air temperature calculated by the model corresponds to the average temperature in the building. In this paper, the reference model is treated as the 'real' building from where the data used to train and test the grey-box, Gaussian process and hybrid models is obtained.

The zone temperature control is done using thermostatic valves for the heating and cooling, which are modelled as proportional-integral (PI) controllers. The average occupancy schedule follows the same pattern as in [9], but with an average peak occupancy of 40 people instead of 25. The actual occupancy differs from the average pattern by a white noise term with a standard deviation of $\sigma = 2$ persons. The shading is automatic and is triggered when the solar irradiation on the façade is higher or equal to 200 W/m^2 [16]. Further details can be found in Table 1.

3. Grey-box model

In order to reduce the modelling effort, the grey-box model is simplified as much as possible. This includes lumping nodes and parameters, linearizing heat transfer equations and ignoring certain physical phenomena. A brief description of the grey-box model and its simplifications is presented next.