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Context-based thermodynamic modeling of buildings spaces

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ABSTRACT

Thermodynamic models are frequently used for modeling the thermal behavior of building spaces. However, the occurrence of events such as, for example, doors, windows and blinds being opened or closed, can drastically affect the underlying processes that govern the dynamics of temperature evolution of building spaces, rendering current thermodynamic models less effective for control and prediction. This article presents a framework for appropriate model structure and parameter selection that accounts for such discrete disturbances based on the notion of context. Contexts are modeled as discrete configurations, capable of representing different thermodynamic behavior models for a building space. Depending on how context changes, our thermodynamic model transitions through a set of different linear time-invariant sub-models. Each sub-model is effective in representing the thermal behavior of the space under a given context and the result is a hybrid automaton that effectively adjusts to the discrete and continuous dynamics of the building environment. We present an application example and use the outputs of EnergyPlus as reference for model performance evaluation. We show, through different context changes, how a context-based model can be used to represent, with reasonable accuracy, the evolution of temperatures in a simulated thermal zone.

1. Introduction

The development of adequate models to capture the dynamics of a building, especially the heat dynamics of building thermal zones (TZs) for controlling indoor climate and improving energy efficiency, has fueled a great deal of research. Models are applied to building simulation and analysis problems including passive design [1,2], energy use [3], and to derive predictive controllers for the building's thermal dynamics [4–7].

Environmental conditions inside a TZ depend on a plethora of factors including zone architectural characteristics, construction materials, climate, occupancy and activities, and the state of electric equipment and temperatures in adjacent zones. Finding the appropriate thermal-dynamics relating the control signals to average zone temperatures is a complex task, due to the complexity of the underlying physical processes [8]. Building environments are continuously changing with the occurrence of events such as, for example, doors, windows and blinds being *open* or *closed*. When a building is divided into environmental zones with occupancy-based heating, ventilation and air conditioning (HVAC) control and temperatures adjusted to occupants comfort preferences (HVAC zoning [9]), an *open* door will increase inter-zonal air-flow rate due to natural convection between two adjacent zones. Changes in the configuration of the environment affect the underlying processes that govern the dynamics of temperature evolution of building spaces. Luo and Ariyur showed, through simulation, that better modeling of the TZ environment, with more sensors to detect the state of doors and windows, can help reduce the use of building energy more than 20% [10]. Therefore, models should take into account these changes.

Using highly detailed physical models for prediction makes many approaches to solving energy management and control problems prohibitively large and complex, rendering them unusable for real-time applications. To circumvent this problem, several authors use simplified and reduced models [11–15]. The purpose of model size reduction is to derive a low-order model of an intrinsically complex system to achieve a reduction in terms of computation effort, while preserving as much of the dominant dynamic description of the original system as possible. Methods for model reduction include, for example, selecting the appropriate time constants of the system [16], or selecting system modes according to their energy contribution [13]. For some modeling tasks a model should be detailed enough to provide a reliable representation of the TZ with a fast time-scale to control, for instance, the rapid flow of heat

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Nomenclature

$\mathcal{A}, \mathcal{B}, \mathcal{C}, \mathcal{D}$	model matrices
$\dot{Q}$	energy flux (heat gain) (W)
$\dot{Q}_s$	solar gains on the outer face of the building envelope ($W\,m^{-2}$)
$\dot{Q}_{sw}$	solar gains transmitted through building windows (W)
f_{sw}	heat transmission function ($\dot{Q}_{sw}$ to zone air) (W)
ρ_{air}	density of air ($kg\,m^{-3}$)
$\dot{Q}_i$	energy flux generated by each occupant (W)
$\dot{Q}_h$	heat generated by heating equipment (W)
C_p	specific heat capacity ($J\,kg^{-1}\,K^{-1}$)
h_c	convective heat transfer coefficient ($W\,m^{-2}\,K^{-1}$)
D	set of opening factor for doors
dof_i	opening factor state of door i
W	set of opening factor for windows
wof_i	opening factor state of window i
WS	set of opening factor for window shades
Heat	set of heater states
$\dot{M}_v$	set of discretized ventilation levels
$\dot{M}_v$	ventilation airflow rate ($kg\,s^{-1}$)
o	number of occupant in the thermal zone
l	discrete control state/*context*
$\rho = (l, x)$	full state
ws_i	opening factor state of the shades in window i
h	the state of the heater
L	set of contexts
$Init$	set of initial states
D	domain
E	set of edges
G	guard condition
Rst	reset map
χ	execution of a hybrid automaton
χ_{EP}	simulation execution
χ_{Model}	model execution
Δx	thickness (m)
λ	thermal conductivity ($W\,m^{-1}\,K^{-1}$)
ρ	density ($kg\,m^{-3}$)
T_a	outdoor ambient temperature (°C)
T_{in}	indoor zone air temperature (°C)
T_g	ground temperature (°C)
T_h	temperature of the heater (°C)
R_{ext}	exterior surface convective resistance ($K\,W^{-1}$)
R_{int}	interior surface convective resistance ($K\,W^{-1}$)
R_W	thermal resistance of windows ($K\,W^{-1}$)
R_{WS}	thermal resistance of window shades ($K\,W^{-1}$)
R_{ih}	thermal resistance heater/interior air ($K\,W^{-1}$)
R_{vent}	resistance for natural ventilation ($K\,W^{-1}$)
C_h	heat capacitance of the space heater ($J\,K^{-1}$)
C_z	thermal capacitance of zone air ($J\,K^{-1}$)
C_{air}	specific heat capacity of air ($kJ\,kg^{-1}\,K^{-1}$)
A_{wind}	window area off the TZ (m^2)
A_e	area affected by $\dot{Q}_s$ (m^2)
A_{roof}	area of the roof (m^2)
x	continuous state
y	model outputs
t	time variable
τ_i	time instant i
τ	hybrid time set
u	model inputs
I	time interval
$\lvert x\rvert$	absolute value of $x \in \mathbb{R}$
$\lVert x\rVert$	L_2-norm of $x \in \mathbb{R}^n : \lVert x\rVert = \sqrt{\left(\sum_{i=1}^{n} \lvert x_i\rvert^2\right)}$
$\lVert x\rVert_\infty$	L_∞-norm of $x \in \mathbb{R}^n : \lVert x\rVert_\infty = \max_{i=1,\ldots,n} \lvert x_i\rvert$

Acronyms and abbreviations

AmI	ambient intelligence
RC	resistance–capacitance
TZs	thermal zones
HVAC	heating ventilation and air conditioning
MAE	mean absolute error
MAX	maximum absolute error
MPC	model predictive control

in a small room. In other situations, a slow time-scale model is enough to predict the mean temperature in the zone over each hour. Model reduction is always a compromise and the relative importance of various system characteristics is highly dependent upon the application. For this reason, Savo and Andrija state that there can be no universal model reduction algorithm and state that “a reduced model is valid only over the range of conditions used to generate it” [17]. Therefore, notwithstanding the potential use for real-time applications, a reduced model fails to cover with efficiency a broad range of conditions that would have to be described either by adding complexity to the model, or by using several different simplified models, with each model adapted to the range of conditions used to generate it.

In this article we show how model reduction can be context-dependent, i.e., model parameters and structure depend on specific conditions that are relevant for a model during a certain time frame. A *context* can be associated, for example, with the activation of an additional heater in the TZ, if the outdoor temperatures reaches below a certain level. Different contexts are associated with different dynamics. Instead of using a single thermodynamic model for the TZ, we use a set of models and use *context* as a concept to define the range of validity for each model. This range can depend on the state of discrete input variables that affect heat exchange, such as the position of window shades, and the opening of windows, or it can depend on values of a continuous variables such as, e.g., solar radiation, air-flow rate, and indoor temperature. This idea has been only superficially explored in the literature. Yashen Lin et al. state that convective heat transfer through the open door has a significant effect on the TZs thermal dynamics and showed that a door status sensor is required for temperature prediction [8]. For model-based control the authors use two different models calibrated with data obtained in different door states (*opened*/*closed*), and use the door status signal to switch between these two models.

Most approaches in the literature address discrete changes in the building environment as disturbances, using statistical methods and stochastic frameworks to create models [18–22] and other closed loop control strategies [23]. However, we conjecture that in many situations models could be more adjusted to context. We show that if the boundary conditions that render some models more appropriate than others are observable and previously known, a context-based framework as a model selection strategy can be a very flexible solution for immediate model commutation. This approach can complement, or even replace, multi-stage model selection strategies such as the ones presented by Prívara et al. [24] and Bacher and Madsen [25,26]. These strategies start with a set of initial candidate models for the TZ with different orders. The maximum likelihood estimation is used to adjust each model parameters to optimal values for prediction, and the likelihood function value is used to compare performance