Energy and Buildings 97 (2015) 86–97

Contents lists available at ScienceDirect

Energy and Buildings

journal homepage: www.elsevier.com/locate/enbuild

A neural network-based multi-zone modelling approach for predictive control system design in commercial buildings

Hao Huang*, Lei Chen**, Eric Hu

School of Mechanical Engineering, The University of Adelaide, SA 5005, Australia

ARTICLE INFO

Article history:
Received 1 September 2014
Received in revised form 21 March 2015
Accepted 21 March 2015
Available online 2 April 2015

Keywords:
Multi-zone modelling
Artificial neural networks (ANNs)
HVAC
Predictive control

ABSTRACT

Predictive control techniques for heating, ventilation and air conditioning (HVAC) systems have been paid an increasing attention in recent years. Such methods rely on building models to accurately predict indoor temperature and make optimal control decisions. Obtaining building models is challenging, as buildings' thermal dynamics are nonlinear, have long time delays, and contain uncertainties. Previous studies on building modelling work mostly focused on small-scale buildings and single-zone cases. They do not accommodate some important features of real-world commercial buildings, such as the effects of thermal coupling between adjacent zones. This paper presents an artificial neural network (ANN) model-based system identification method to model multi-zone buildings. The proposed model considers the energy input from mechanical cooling, ventilation, weathher change, and in particular, the convective heat transfer between the adjacent zones. The testing of the temperature history shows that the proposed ANN model captures the thermal interactions between the zones reasonably well, therefore achieves more accurate prediction results than a single-zone model. Based on the model, a simple yet effective model-based predictive control method is developed, with the results showing that comfortable temperature can be maintained with reduced energy consumption.

1. Introduction

Buildings are responsible for 40 per cent of the energy consumption and 33 per cent of carbon dioxide emissions in the world. Within buildings, almost half of the energy use is related to heating, ventilation and air conditioning (HVAC) systems [1]. Reducing the building energy costs has become an urgent task, due to the increasing environmental concerns and energy prices. Despite of this fact, HVAC systems at the existing buildings are not operating in the most efficient ways. Therefore, this study aims to develop a building modelling approach, which is suitable for the design of predictive control strategies in commercial buildings. The control strategy can be used to reduce the energy consumption and improve thermal comfort in the buildings.

Most current, proportional-integral-derivative (PID) control and on/off control are being widely used for commercial HVAC systems. They use current measured temperatures as the inputs to control local actuators, such as chilled water valves and mechanical dampers. However, since building dynamics have strong thermal inertial, the indoor temperature may delay in response to the control actions. This causes a waste of energy use and poor thermal comfort. In recent years, researchers have shown that predictive control strategies can significantly reduce the energy costs associated with HVAC systems, through both simulation [2–6] and experimental studies [7–10]. Predictive control allows one to take advantage of weather forecast and occupancy prediction to reduce energy costs and improve thermal comfort. In general, predictive control can be regarded as an integration of different supervisory control methods, such as optimal start–stop control [6], load shifting control [11] and demand-limiting control [12]. The most crucial step of implementing such a control strategy is to create a thermal dynamic model, able to accurately predict changes in the building temperature. For control purpose, the model should have simple structure and be suitable for a wide operational range. However, building modelling is challenging, for several reasons. The complexities of building dynamics modelling are listed as below:

1. A building's operational environment is a time-varying system with many uncertain variables. For example, a sudden change in the number of occupants or accumulated change in solar gain will cause fluctuation of indoor temperature.

* Corresponding author.
** Corresponding author. Tel.: +61 883135469.
E-mail addresses: h.huang@adelaide.edu.au (H. Huang), lei.chen@adelaide.edu.au (L. Chen).

http://dx.doi.org/10.1016/j.enbuild.2015.03.045
0378-7788/

Nomenclature

C_z	thermal capacitance associated with the fast-dynamic masses (kJ/°C)
C_w	thermal capacitance associated with the slow-dynamic masses (kJ/°C)
C_a	specific heat of air (kJ/kg°C)
T	thermal node temperature (°C)
T_c	chilled water temperature (°C)
T_{sp}	set point temperature (°C)
T_{up}	upper comfort band (°C)
T_{low}	lower comfort band (°C)
R	thermal resistance associated with walls, window or floor (°C/W)
H_r	relative humidity (%)
S_r	global horizontal irradiation (W/m^2)
R_c	convective heat transfer coefficient between adjacent zones (°C/W)
$\dot{m}$	mass flow rate of the supplied air (kg/s)
Q	internal and external heat gain generated by solar radiation (Q_s), leakage (Q_l) and occupants (Q_p) (W)
V_c	chilled water valve opening level (%)
D_{out}	outdoor air damper opening level (%)
P_c	power consumption of cooling coils (kW)
P_f	power consumption of supply fan (kW)
COP	coefficient of performance of the chiller plant
Δt	sampling time of the building data (s)
k	time step
n_a, n_b	orders of the input variable
r	order of the system
n_k	time delay of the input variable
f	nonlinear neural network function

Subscripts

i	indices for zones
sa	supply air
r	return air
out	outdoor air
w	walls and ceiling
g	windows
N	predction horizon

Greek letter

ρ	density of the air (kg/m^3)

2. Air-conditioned buildings possess several nonlinear variables, such as temperature, relative humidity and outdoor air damper actions, which are difficult to model using the standard methods (such as the simplified physical model).
3. HVAC systems have several coupled control processes that cannot be treated independently. For example, air handling unit (AHU) processes are affected by the chilled water temperature changes and flow-rate fluctuations.
4. The internal space of buildings is divided into adjacent zones, each controlled by an individual AHU. The temperatures of the individual zones are not uniform, and are coupled, which makes building modelling a multiple-input, multiple-output (MIMO) problem.

A variety of approaches has been proposed for modelling the thermal dynamics of the buildings. Probably the most commonly used one is resistance-capacitance (RC) networks, which is based on the first principle of thermal dynamics. The use of RC models for model predictive control (MPC) has been applied to several building energy studies [11,13–16]. RC networks use lumped capacitance and resistance in an analogy electric circuit to represent the thermal elements of a building. When a multi-zone building is considered, RC networks can model heat transfer among zones by linking a series of linear differential equations [17,18]. For example, Goyal et al. [19] model inter-zone convection of a building with RC networks. They conclude that the temperature predicted by the RC model that includes convection effects is closer to the measured temperature than those by the model that considers conductive heat transfer only. However, applying simplified RC model to convective heat transfer among the zones can cause model mismatch, mainly because the uncertain coupling effects between zones can hardly be identified by the simplified RC models.

Statistical models derived from system identification methods have also been investigated. This includes autoregressive with the exogenous (ARX) model [20], autoregressive moving average model with exogenous inputs (ARMAX) model [21] and subspace model [7]. For example, Morosan et al. [20] presented a distributed model predictive control strategy for a multi-zone building with intermittently operating mode. They found that the distributed MPC which considers the thermal interaction among zones outperforms the MPC which does not consider thermal interaction. However, because the statistical models are linear, time-invariant, they can easily lose accuracies when strong nonlinearity and uncertainties are presented at the systems. Therefore, growing attention has also been paid to artificial neural network (ANN) models, for building modelling and control [22–25]. ANN models are suitable for building dynamics modelling due to their abilities to deal with nonlinear, multivariable modelling problems. Different from the physical models, the parameters of ANN are the number of neurons and the values of interconnection weights and biases. If a dynamic ANN model is employed, the orders and delay terms should also be considered during the model development.

Several studies have proven ANN models superior to linear models [22,26] and physical models [23,27] in modelling the nonlinear HVAC systems. Using a feed-forward neural network, Lu and Viljanen [26] constructed a nonlinear autoregressive with external input (NARX) model to predict both indoor temperature and relative humidity. Ruano et al. [23] incorporated a radial basis function neural networks to build an adaptive model to predict indoor temperature of a school building. Ferreira et al. [24] tested an ANN based model predictive control at a campus building, and applied a discrete branch and bound approach to optimise the energy usage. Spindler and Norford [27] built a multi-zone, multi-node ANN model to predict indoor temperature in a multi-zone residential building. The accuracy of the predictive model is smaller than the ones obtained in other similar studies. In ref. [28], a predictive control method was developed to determine the optimal cooling mode, which results in a reduced fan energy usage while maintaining a comfortable temperature. Garnier et al. [6] built an ANN model-based predictive control strategy to satisfy the thermal comfort index of a non-residential building. The result shows that the predictive controller which considers the heat transfer between the adjacent rooms offers improvement in both energy efficiency and thermal comfort.

In summary, previous studies focusing on neural network modelling have largely considered multi-input, single-output (MISO) structures for single zones. The effects of thermal interactions, such as convective heat transfer between zones, have rarely been addressed. Multi-zone modelling using ANN models can be found in [6,27]. However, the effects of thermal interaction between zones on the modelling accuracies have not been discussed in detail by these studies. It is believed that with enough building data, ANN models are able to model effectively the thermal interaction between the zones, towards the achievement of a MIMO model with better prediction accuracy and generalisation