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A general multi-agent control approach for building energy system optimization

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ABSTRACT

Penetration of advanced building control techniques into the market has been slow since buildings are unique and site-specific controller design is costly. In addition, for medium- to large-sized commercial buildings, HVAC system configurations can be very complex making centralized control infeasible. This paper presents a general multi-agent control methodology that can be applied to building energy system optimization in a “plug-and-play” manner. A multi-agent framework is developed to automate the controller design process and reduce the building-specific engineering efforts. To support distributed decision making, two alternative consensus-based distributed optimization algorithms are adapted and implemented within the framework. The overall multi-agent control approach was tested in simulation with two case studies: optimization of a chilled water cooling plant and optimal control of a direct-expansion (DX) air-conditioning system serving a multi-zone building. In both cases, the multi-agent controller was able to find near-optimal solutions and significant energy savings were achieved.

1. Introduction

More than 40% of the primary energy usage in the United States is related to energy consumption in buildings [1] and if buildings are not operated properly, a significant amount of energy is wasted. The energy savings opportunities for optimal building controls are becoming widely recognized leading to growing research efforts in the past few years. However, the deployment of advanced controls in buildings has been progressing very slowly due to several reasons: (1) buildings are unique in terms of both building construction and heating, ventilation and air-conditioning (HVAC) system configuration, which makes building-specific controller design costly; (2) optimal control of complex building energy systems is difficult because of the nonlinearities in the models as well as the large number of optimization variables.

Multi-agent control is a promising solution for building energy system management due to good modularity and performance in solving large-scale problems. Several efforts have been made to solve different building control problems using a multi-agent system. For example, some previous work focused on implementation of intelligent agents where the intelligence comes from some heuristic rules that already existed for specific types of components [2–4]. As an example, Davidsson and Boman [3] utilized a room agent to setup or setback the room temperature setpoint depending on the presence of occupants to reduce HVAC energy consumption. A number of heuristic control strategies for different types of building energy systems can be found in Chapter 42 of the ASHRAE handbook—HVAC applications [5], and also in Refs. [6–8]. Although heuristic- or rule-based control is simple to implement and typically can be easily integrated within a device agent, general heuristic control rules do not exist for most HVAC devices and thus, the application of rule-based controls in a multi-agent controller is limited.

Some other researchers adopted a centralized-optimization-based multi-agent control approach, which mainly takes advantage of the good modularity of a multi-agent control system [9–11]. As an example, Zhao et al. [9] proposed a multi-agent control structure with an electricity agent (E-agent), a heating agent (H-agent) and a cooling agent (C-agent) where the E-agent manages the electrical power flow from electricity generator and the energy consumers are handled by the H-agent and C-agent. The decision making process therein still relies on centralized optimization and thus, this control approach may not be suitable for control of complex building energy systems.

Other work has investigated distributed decision making within a multi-agent controller to achieve good scalability. Most of the

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Nomenclature

A_{damper}	Damper cross sectional area (m^2 or ft^2)
A, C	State-space matrices
$\mathbf{B}_w, \mathbf{B}_u$	State-space B matrices corresponding to disturbance and control inputs, respectively
c_p	Specific heat of air (kJ/kg-K or btu/lb-F)
ESP	External static pressure of fan (in. W.C. or Pa)
m_a	Air mass flow rate across the cooling tower or DX coil (Kg/s or lb/s)
$m_{a,i}$	Air mass flow rate through VAV box *i* (Kg/s or lb/s)
m_{co}	Condenser water mass flow rate mass flow rate (Kg/s or lb/s)
m_{cto}	Cooling tower outlet water mass flow rate (Kg/s or lb/s)
m_{mains}	Make-up water mass flow rate (Kg/s or lb/s)
Pow	Power consumption (KW or btu/hr)
P_{ma}	Cooling coil inlet air pressure (in. W.C. or Pa)
P_{sa}	Fan outlet air pressure (in. W.C. or Pa)
$P_{z,i}$	Air pressure in zone *i* (in. W.C. or Pa)
Q_{ev}	Chiller load (KW or btu/hr)
SHR	Sensible heat ratio of cooling coil
Stage	Compressor stage
T_{amb}	Ambient air (dry-bulb) temperature (°C or °F)
T_{coi}	Condenser inlet chilled water temperature (°C or °F)
T_{coo}	Condenser outlet chilled water temperature (°C or °F)
T_{cto}	Cooling tower outlet chilled water temperature (°C or °F)
T_{db}	Ambient air dry-bulb temperature (°C or °F)
T_{evo}	Evaporator outlet chilled water temperature (°C or °F)
T_{la}	Cooling coil outlet air temperature (°C or °F)
T_{sa}	Supply (fan outlet) air temperature (°C or °F)
T_{wb}	Ambient air wet-bulb temperature (°C or °F)
T_{mains}	Make-up water temperature (°C or °F)
$\mathrm{T}_{z,i}$	Air temperature of zone *i* (°C or °F)
w_{ma}	Cooling coil inlet air humidity ratio (kg water/kg air)
X	Vector of all local copies of the design variables
$\mathbf{x}_k, \mathbf{y}_k$	State and output vectors at time step *k*
Y	Dual variable vector
$\mathbf{y}_{k+1}^{sp}$	Output setpoint vector at time step k+1
Z	Vector of the design variables
$\mathbf{X}_i, \mathbf{Y}_i$	Sub-vector corresponding to sub-problem (*i*)
α	Step size for dual update
θ_i	Damper opening in VAV box *i* (%)
ρ	Air density (kg/m^3 or lb/ft^3)
σ	Factor for the augmented multiplier
ε	Convergence threshold

Subscripts

chiller	Chiller
ct	Cooling tower
DX	DX unit
fan	Fan
pump	Pump

Superscripts

(*i*)	The *i*th copy of the corresponding local variable
[*i*]	The *i*th iteration of optimization

work under this category focused on dynamic optimization problems under a distributed model predictive control (DMPC) scheme. Some examples can be found in Refs. [12–14]. However, most of these studies were primarily concerned with optimal load profile management and the HVAC system models were over simplified. This could reduce the actual energy savings since there are significant savings opportunities with optimal coordination of HVAC components (see Ref. [15] as an example).

The present study proposes a general multi-agent control approach for building energy systems that consists of two main elements: a multi-agent control framework and a multi-agent decision making procedure. Once a control project is configured within the framework for a building energy system, a centralized or distributed optimization problem is automatically composed depending on the user's specification and some symbolic manipulations are performed to eliminate the redundant design variables and equations. If the distributed control option is chosen, two different consensus-based optimization algorithms that are embedded within the framework are used to drive the intra-agent optimization and inter-agent coordination processes. The overall approach addresses the issues of low implementation cost and scalability in the following ways:

1 *Low implementation cost*: if the component agent models that represent device performance were integrated within HVAC devices (e.g., chillers) by manufacturers (models could adapt on the fly with continuous measurements), the proposed multi-agent control framework would automate the controller design process.
2 *Good scalability*: the distributed decision making process allows solution of a large-scale optimization problem in a distributed and parallel way.

The proposed multi-agent control approach was tested for two building control case studies. One case study focused on optimal control of a chilled-water cooling system and the other one concerned optimization of a direct-expansion (DX) air conditioning system serving a multi-zone building. The performance of the multi-agent control and the corresponding energy savings compared with other benchmarks were evaluated under different operating conditions.

2. Multi-agent control framework

A prototype of the multi-agent control framework was developed using the Matlab object-oriented programming toolkit. It serves as a proof of concept in the software sense but can be replicated easily in other programming environments to support hardware implementation. The framework defines a general component agent structure as well as the flow connections between agents. To synthesize a multi-agent control system, a field engineer would only need to configure the inter-agent connections and the framework would compose the control algorithm automatically, assuming the component agents were integrated within the devices by their manufacturers.

2.1. Agent definition

Fig. 1(a) shows the structure of the backbone for a general component agent. It is written as a super class from which each component class can inherit the basic agent structure. A component agent is essentially an instantiation of the corresponding component class.

The properties of the agent class consist of a collection of cost functions, equality and inequality constraints that characterize the behavior of a specific component. Once a component agent is instantiated, the cost functions and equality/inequality constraints will be registered in the composed optimization(s). Note that if there are multiple cost functions in the same control project, the