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Investigation of the Underlying Mechanism behind Energy Savings Achieved by Building Model Predictive Control

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ABSTRACT

Model predictive control is an important control method to reduce building heating and cooling energy consumptions. However, the mechanism by which the energy savings are achieved is not well understood. This paper investigates such mechanism using building energy simulation. The simulation results show that the better constrained indoor temperature leads to lower heating and cooling loads, which results in reduced energy consumptions. Comparing with a conventional 2 °C dead-band control, a model predictive control, which restricts the indoor temperature within 0.2 °C range of the set point, obtains an 8.5% and a 13.6% annual energy savings in heating and cooling respectively.

Keywords: indoor temperature variation, application of machine learning in buildings, heat pump variable speed control, building model predictive control, advanced HVAC control

NONMENCLATURE

Abbreviations	
ASHRAE	The American Society of Heating, Refrigerating and Air-Conditioning Engineers
COP	Coefficient of Performance
DB	Dead-Band
HVAC	Heating, Ventilation and Air-Conditioning
IEA	International Energy Agency
IECC	International Energy Conservation Code
MPC	Model Predictive Control
GJ	gigajoules
RMSD	Root Mean Square Deviation

1. INTRODUCTION

Based on IEA's estimation, residential and commercial sectors consumed around 86.4 exajoules and 32.8 exajoules of energy globally in 2017 [1]. Together, they count for 29% of world's total energy consumption of 406.8 exajoules. Space heating and cooling are two of the most energy intensive end-uses. They account for around 43% and 8% of the total energy consumption in residential buildings [2], as well as 25% and 9% in commercial buildings [3] in the U.S. according to U.S. EIA. In addition, the energy consumptions for space heating and cooling are expected to grow globally due to increasing demand.

In order to secure a sustainable future, countless efforts have been made to reduce the building energy consumption by both academic researches and industrial applications. Some of these efforts focus on improving the building envelope while others target the end-use equipment like HVAC systems. HVAC system-based efficiency measures can be further categorized into hardware-based and control-based approaches. The deployment of the hardware-based efficiency measures has been slow due to its heavy front-cost nature. For example, the average residential main heating equipment efficiency stayed the same at around AFUE 0.8 between 2007 and 2019 in the U.S. [4]. The software-based approach, on the other hand, is moving much faster. As an example, in the U.S., the number of homes with a smart thermostat has experienced a 64% annual growth to 7.8 million in 2016 [5].

Among the control-based approaches, Model Predictive Control (MPC) has been a hot topic recently due to the accuracy boost from machine learning algorithms. The MPC is commonly used for minimizing energy consumption, maintaining thermal comfort, and

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ensuring indoor air quality, etc. [6]. In terms of its energy reduction potential, Yang et al. conducted an experimental study and reported around 20% electricity savings for an air handling unit with a dedicated outdoor air system [7].

While there are considerable numbers of researches on the machine learning centered MPC, some of which focus on the algorithms [8], some on implementation and integration [9], and some on grid level demand management [10], there has never been a detailed investigation of the exact reason how a MPC saves energy in HVAC systems. Is it because the MPC allows the HVAC equipment to operate at higher efficiency? If so, what mechanism causes the efficiency gain? Or is it caused by lowering building conditioning demands? If so, how does a control algorithm reduce the building heating or cooling load? Despite reports from both simulations and experiments, the underlying mechanism by which the MPC saves energy in buildings need to be thoroughly understood in order to realize its full potential.

This article aims to answer these questions through the whole building energy modeling with MPC on a simplistic but realistic stand-alone residential house conditioned by a heat pump. This simulation centered study will provide detailed data on the operations of the heat pump as well as the overall building thermal loads.

2. METHODOLOGY

2.1 Building Energy Modeling

This study relies on a few key components including a simulation engine, a realistic building model, the implementation of MPC, as well as a comparison with the conventional dead-band (DB) based control.

EnergyPlus, a well-respected whole building energy modeling engine, is used to perform the simulations. To capture the details in the HVAC operations and the building thermal behaviors, the simulation timestep is set to be 5 mins.

To avoid the complexities introduced by commercial buildings due to their wide varieties of energy use profiles, this study focuses on a typical residential house in the U.S. The house model, which complies with the IECC 2006 and comes with a full set of appliances and occupancy profiles, is sourced from the residential prototype building models [11]. New York City, whose humid subtropical climate is represented by TMY3 data [12], is chosen as the location of this study. The performance of the heat pump comes from the Carrier 25VNA [13] with a rated COP of 4.5 in heating and 3.9 in cooling at standard rating conditions. It provides both heating and cooling and is sized to handle the full load of the house without an auxiliary heater.

Instead of implementing the MPC independently, a unique feature of the simulation engine is exploited to imitate such control strategy. EnergyPlus calculates the thermal zone demand, the HVAC system supply, and reconciles the energy balance through successive iterations in each timestep. Therefore, the building heating and cooling loads are already predicted within the simulation engine. The accuracy of the predictive control can be tuned by the dead-band setting.

2.2 Dead-Band and MPC

This study centers on the concept of the thermostat dead-band. It is the difference between the cut-in and cut-out temperature of heating or cooling operation. For example, a thermostat with a 2 °C DB and 20 °C heating set point will call for heating at 20 °C indoor temperature and turn off heating when temperature reaches 22 °C. It is a way for vast majority of conventional thermostats to resolve the contradiction between a constant indoor temperature and a proper HVAC operation. If the DB is small, the HVAC system is likely to be on short cycling, which leads to efficiency and product lifespan degradations [14]. Whereas a large DB will result in significant indoor temperature swing therefore thermal discomfort.

Unlike the conventional DB control, MPC takes advantage of the advanced modulating capability of modern HVAC equipment and directly predicts the instant building thermal loads and dictates the operating capacity of HVAC equipment. This results in a more stable indoor temperature while avoiding the short cycling. In order to isolate key variables in the study, the cycling loss, which is well-understood [14], is not taking into account. Therefore, the control strategies can be characterized based on DB width from 0.2 °C to 4 °C as shown in Fig. 1. The DB width represents the accuracy of the MPC. As the width narrows, it emulates a more accurate MPC due to a tighter constrained indoor temperature. The thermostat setpoint is 20 °C for heating and 25.6 °C for cooling. The heating season is set to be before May 27th and after Oct. 6th, while the cooling season is the period in-between.

3. RESULTS AND DISCUSSION

The main results of this study can be summarized into two box charts as shown in Fig. 3 and Fig. 4. They illustrate the indoor temperature variation profiles during heating and cooling seasons respectively. The DBs with 2, 3, and 4 °C represent the conventional control. Whereas the DBs with width 1, 0.5, and 0.2 °C represent the MPC with increasing accuracy.

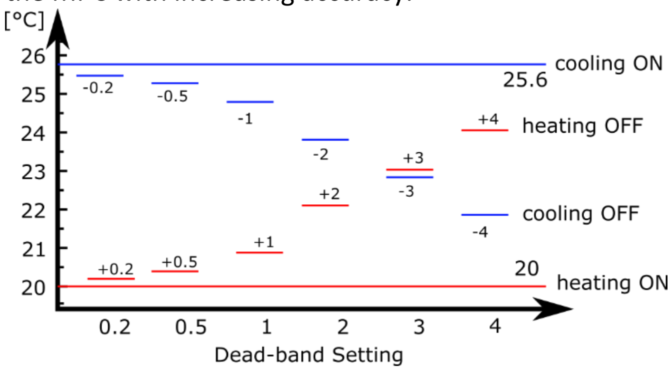

Fig. 1: Heating and cooling DB settings

The MPC attends to match the operating capacity of the heat pump with the heating or cooling demand of the house, which leads to a more constrained indoor temperature. As Fig. 2 shows, the MPC (0.2 DB) allows the heat pump to match the instant building heating and cooling demands, whereas the 4 °C DB control relies on ON/OFF cycling to keep indoor temperature within the range.

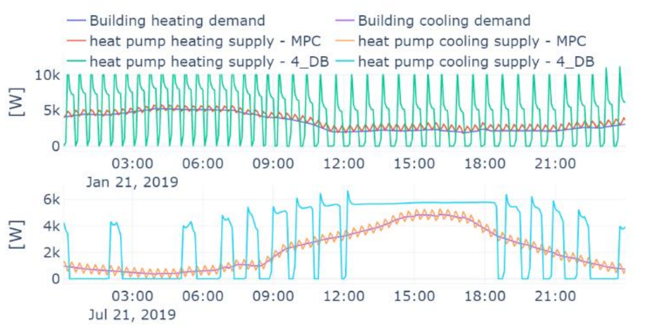

Fig. 2: Building demand & supply in heating / cooling on ASHRAE winter and summer design day

In heating seasons, the MPC can restrict the indoor temperature closer to the set temperature of 20 °C. As a result, not only does the indoor temperature become more stable, but also stays lower overall. For example, the median indoor temperature decreases gradually from 23.3 °C in the 4 °C DB scenario to 20.4 °C in the 0.2 °C DB scenario as shown by the dropping median lines inside the interquartile boxes in Fig. 3.

Whereas in cooling seasons, the MPC keeps the indoor environment closer to the set temperature of 25.6 °C with less variations. With DB reducing from 4 °C to 0.2 °C, the median indoor temperature increases from 23.6 °C to 25.4 °C.

Other than how well the controls constraint the indoor temperature, their accuracy can also be evaluated by RMSD between the instantaneous building heating or cooling demand and heat pump supplies as show in Table 1. For example, the 4 °C DB control has about four times larger RMSD than the 0.2 °C DB control during the heating season.

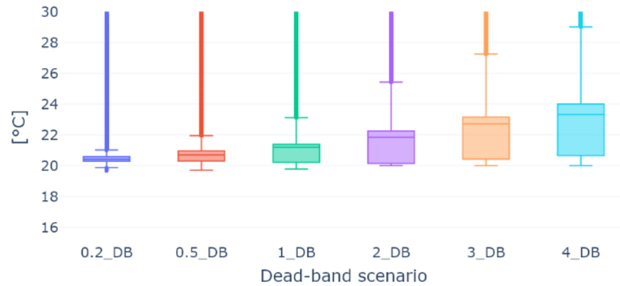

Fig. 3: Indoor temperature profile during heating seasons

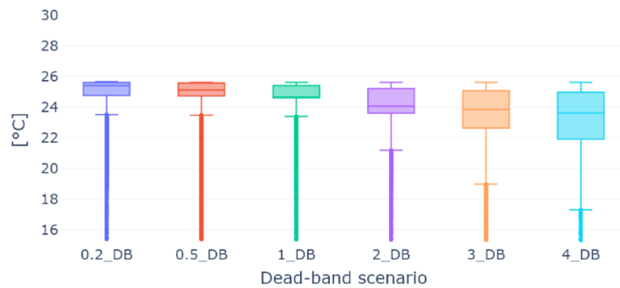

Fig. 4: Indoor temperature profile during cooling seasons

Table 1: Control accuracies evaluated with RMSD between instant building demand and heat pump energy supply

[W]	0.2_DB	0.5_DB	1_DB	2_DB	3_DB	4_DB
heating	902.1	1,197.1	1,739.0	2,740.0	3,301.0	3,893.4
cooling	224.1	524.7	945.6	1,626.1	1,969.6	2,181.8

The lower overall indoor temperature in heating seasons, which is achieved by MPC, leads to lower total building heating load therefore reduced heating energy consumption by the heat pump. As Fig. 5 indicates, the total annual heating load drops by 15.2% from 72.5 GJ in the 4 °C DB scenario to 61.5 GJ in the 0.2 °C DB scenario. Consequently, the total heating energy consumption decreases from 25.5 GJ to 19.9 GJ. In addition, since the overall temperature difference between the indoor and the outdoor environments becomes smaller with smaller DB, the average heating COP of the heat pump improves by 10.7% from 2.8 to 3.1.

Similar trend is observed in cooling as shown in Fig. 6. The total annual cooling load and its energy consumption drops to 15.3 GJ and 4.5 GJ respectively as the DB narrows to 0.2 °C. Meanwhile, the average cooling COP increases by 5.9% from 3.2 to 3.4.

As the simulation results reveal, the MPC directly reduces the building heating and cooling loads by constraining the indoor temperature close to the set point through matching building thermal loads with the heat pump capacity. For conventional DB based control, the DB width is commonly set to 2 °C or larger in order to prevent frequent cycling which causes damage to the equipment and introduces cycling loss.

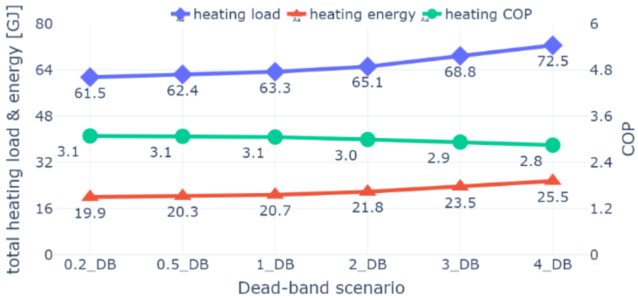

Fig. 5: Total annual building heating load, heat pump energy consumption and the average COP

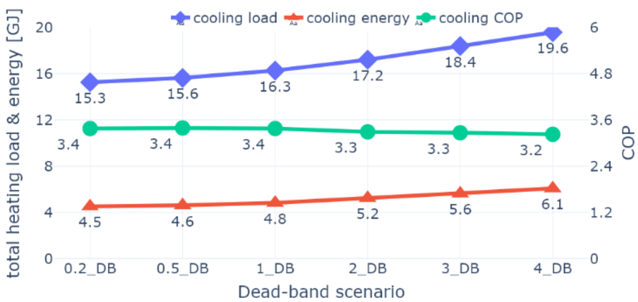

Fig. 6: Total annual building cooling load, heat pump energy consumption and the average COP

Pairing with modulating capability, MPC fits the HVAC equipment heating or cooling energy supplies with the building thermal demands. This helps to avoid short cycling, reduces the total heating and cooling loads, and improves operating COP of the heat pump slightly. Therefore, better constrained indoor temperature is one of the main mechanisms by which the MPC saves energy. Additional energy is also saved with the improved COP of the heat pump. Comparing with a conventional 2 °C DB control, the MPC, which confines indoor temperature variations within 0.2 °C, leads to an 8.5% and a 13.6% annual energy savings in heating and cooling respectively.

4. *CONCLUSIONS*

This paper investigates the mechanism by which the model predictive control (MPC) saves energy in buildings through simulations. The results reveal that the better constrained indoor temperature leads to lower heating and cooling loads therefore energy savings. In addition, small improvements in the average Coefficient of Performance (COP) can be observed in the heat pump operation due to lowered overall temperature difference between the indoor and the outdoor environments.

Comparing with the conventional dead-band (DB) based control, not only do model predictive control leads to energy savings, but also help to avoid short cycling. The total benefits, which include reduced cycling losses related to specific heat pump designs, will be studies in the future.

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