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Original Article

Simulation-based Short-term Model Predictive Control for HVAC Systems of Residential Houses

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Abstract: In this paper, we propose a simple model predictive control (MPC) scheme for Heating, ventilation, and air conditioning (HVAC) systems in residential houses. Our control scheme utilizes a fitted thermal simulation model for each house to achieve precise prediction of room temperature and energy consumption in each prediction period. The set points for each control step of HVAC systems are selected to minimize the amount of energy consumption while maintaining room temperature within a desirable range to satisfy user comfort. Our control system is simple enough to implement in residential houses and is more efficient comparing with rule-based control methods.

Keywords: Model predictive control, air conditioning, thermal simulation.

1. Introduction

With the development of computer and network technologies, a new paradigm of Internet of Things (IoT) that things around us such as sensors, electrical devices, ... will connect into a network gradually becomes a reality. In such an environment, information of physical space obtained by sensors can be sent into cyber space (i.e. computers), which computes the status of the physical space and optimizes the control of actuators on the physical space in order to reduce the operation cost of the whole system. Such kind of systems is called cyber physical systems (CPSs) [1] and attracts a lot of attentions of researchers.

Smart home services such as air conditioning can bring to us a comfortable living environment, but also consume a large portion of electrical energy. Nowadays, the introduction of a CPS system for smart homes, which may have renewable energy sources, networked appliances and sensors, gives us the ability to increase the efficiency of energy usage in residential houses [2]. Environment data gathered by sensor networks, such as temperature, humidity, solar radiation can be used for predicting the dynamic change of system state and optimizing the operation of HVAC systems. This control method is called model predictive control (MPC).

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MPC control strategies for HVAC systems can adapt more properly to the dynamics of thermal environment than conventional control methods such as on/off control or proportional-integral-derivative (PID) controls.

Many research on predictive model control for HVAC systems have been done recently [3–6]. Though MPC is a promising technology for HVAC system controls, its performance is highly dependent on the accuracy of prediction models. Different thermal models of a house and models of HVAC systems are used to predict the change of thermal environments and energy consumption of HVAC systems in conventional works. However, these models are difficult to apply to a real house since their parameters are difficult to identified. Further, the cost functions used to optimize the operation of HVAC systems must take into account both energy efficiency and user thermal comfort.

We have developed a thermal simulator to simulate the change of room temperature and the amount of energy consumption of HVAC systems for real residential houses. Our simulation can achieve high accuracy due to the identification of thermal-related parameters for each real house based on experimental data [7].

In this paper, we focus on MPC control strategies for HVAC systems in residential houses, which may include a variety of devices such as sensors, air ventilation fans and air conditioners. We propose the utilization of our thermal simulator to precisely predict the change of thermal indoor environment. Our MPC control mechanism optimizes the operation of HVAC systems for short term durations based on both energy efficiency and user thermal comfort. Further, it is simple enough to implement in real house environment. Our evaluation results show that proposed MPC control mechanism can reduce energy consumption significantly comparing with a rule-based control mechanism.

The structure of the paper is follows. In the next section, we will describe the related works and their limitations. We then describe our thermal simulator used to predict the change of thermal environment in Section 3. In Section 4 and 5, we describe our MPC control scheme and performance evaluation of proposed control scheme. The last section concludes the paper.

2. Related works

The application of MPC in controls of HVAC systems are studied in a lot of research works [3–6, 8]. Each of them is different in prediction model, optimization target and case study.

Many research works tries to optimize the operation of HVAC systems based on time-varying electrical price for a long term to minize the operation cost. The authors in the paper [6] have investigated a MPC based supervisory controller to shift the heating and cooling load of a house to off-peak hours for residential houses in Toronto Canada. Sturzenegger et. al. [9] reports the performance of MPC control strategy in a fully occupied Swiss office building. In these works, since the prediction horizon is long, weather forecast data is used to predict the change of thermal environment. In the work [3], the uncertainty due to the use of weather predictions is taken into account in a stochastic MPC strategy.

Energy consumption and thermal comfort are both essential for the control of a HVAC system. Ascione et. el. [10] works on simulation-based MPC procedure which optimizes the hourly set point temperatures of HVAC system in daily operation. In the paper [11], MPC control strategies are applied for a ceiling radiant heating system to adjust the set points of supply water temperature. In the work of J. Hu et. al. [4], MPC control strategies are applied for mixed-mode cooling including window opening position, fan assist, and night cooling, shading. In these papers, the authors try to minimize energy consumption while maintaining the room temperature within a desired comfort range.

Various kinds of thermal models are used to predict the change of thermal environment and energy consumption. The utilization of Building performance simulation tools – e.g., DOE-2 [12], EnergyPlus [13] and TRNSYS® [14] for prediction purpose is studied in several works [10, 15]. However, since they are designed mainly for estimating the energy usage of a building, they cannot be readily used for real-time MPC control schemes. A lot of works calculate room temperature based on RC modelling, which considers a room as a network of first-order systems, where the nodes represent the room temperature or the temperatures in the walls, floor or ceiling [3, 4, 11]. Room temperature is calculated based on heat transmission between nodes. RC modelling is easy to implement, however it is difficult to estimate parameters of models for real houses since the number of parameters is large.

Kwak et. al. [5] and En et. al. [16] develop MPC control frameworks for real-time building energy management systems. These implementations show the feasibility of MPC control mechanism in real building environment.

3. Thermal simulation

In order to simulate the change of indoor temperature of a house, a "black-box" model, or a "grey-box" model, or a "white-box" model can be used. "White-box" models, i.e. detailed physical models, are used in a number of thermal simulators such as DOE-2 [12], EnergyPlus [13] and TRNSYS® [14]. They can evaluate thermal load of a building from the early design phase, however, these models require a large number of detailed thermal parameters to be specified. In the case of modeling real houses, many parameters are uncertain and needed to be estimated by the use of measurement data of external and indoor thermal environment.

In order to predict the energy consumption of HVAC systems and the change of thermal environment in a time period, we utilize a simple thermal model, which calculates the change of room temperature $T_{room}(t)$ based on the total amount of heat flows going out or coming in a room as the following equation.

$$\frac{\partial T_{room}(t)}{\partial t} = \frac{1}{C_v} \sum_i \beta_i Q_i(t) \tag{1}$$

Here, $Q_i(t)$ is the i^{th} heat flow going out or coming in the room at time t and C_v is the heat capacity of the room. β_i is a coefficient which corresponds to the i^{th} heat flow and is determined based on experimental data.

In our thermal model, the heat flow $Q_i(t)$ is calculated based on various physical models which specifies thermal characteristics of a room. These heat flows also depend on several environment parameters including the room temperatures, outside temperature, solar radiation and heat radiation of electrical devices in the room. We calculate several kinds of heat flows going out or coming in a room as follows.

- Conduction heat flow through a wall or a window: We use a unsteady-state heat transfer model to calculate conduction heat flow through a wall. This model can take into account the fast change of temperature at surfaces of walls.
- Solar radiation coming in through a window: We estimate diffuse and direct radiation from sensor data and calculate through a window separately.
- Heat flow created by a HVAC system
- Radiation heat from electrical devices and human bodies.

There are lots of thermal-related parameters required for the calculation of each heat flow. Even though document of home plans and specifications of a house can be obtained, these parameters are not often precisely determined. Hence, the coefficient β_i in Eq. 1 corresponds to the heat flow $Q_i(t)$, which can be considered as a representative parameter for all uncertain

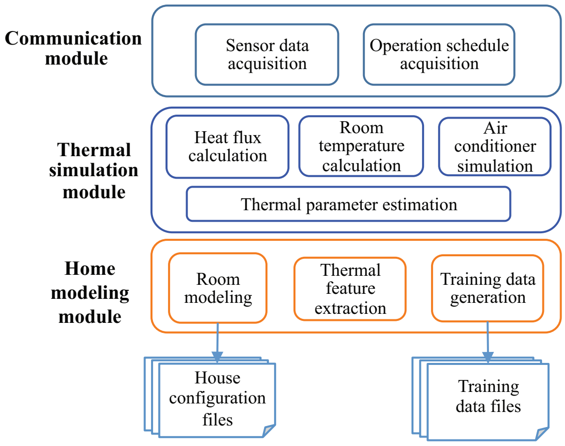

Figure 1. Structure of proposed thermal simulator.

parameters involved in the calculation of the heat flow $Q_i(t)$. We only need to estimate these coefficients, whose number is small, by the use of training data. Therefore, our thermal simulator can achieve high accuracy comparing with actual measurement data.

Our simulator is constructed from three following modules (Fig. 1).

- Home modeling module: models a house as a number of rectangular rooms adjacent to each other and each room contains a number of walls and windows. The module reads parameters related to thermal characteristics of walls and windows from a number of configuration files and creates an object to store the structure information of the house. It also reads offline environment data such as temperature, humidity, wind velocity, data of solar radiation as training data from sensor data files.

- Thermal simulation module: The module calculates the change of room temperature by calculating conduction heat, solar radiation, radiation heat from electrical devices and heat removed or generated by air conditioners. We uses training data to identify unknown thermal parameters of thermal models.

- Communication module: This module gets data from sensor installed in a house and gets weather forecast data from an online weather station. It then sends the data to the thermal simulation module to perform online prediction of energy consumption.

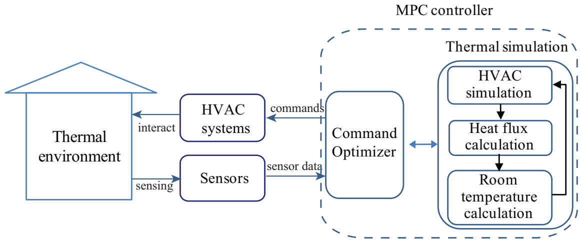

Figure 2. System model of MPC controller for HVAC systems.

4. Model predictive control for HVAC systems

4.1. System model

System model for MPC controller of HVAC systems is shown in Fig. 2. The system includes following elements.

- Sensors installed in a house which collect environment data and send to a MPC controller. The sensor data may include the data of outside temperature, outside humidity, solar radiation, ...

- HVAC system which interacts with the thermal environment of the house. A HVAC system may include air conditioners, heaters, ventilation fans, curtain controllers, ...

- MPC controller which receives data from sensors and selects optimized control set for the HVAC system based on the prediction results of a thermal simulator

- Thermal simulator which gets input data from MPC controller and predicts the change of room temperature and the amount of energy consumption of the HVAC system. The input data includes sensor data and command sets for the HVAC system

We consider a HVAC system for residential houses which includes air conditioners, which consume electrical energy to produce heating energy or remove thermal energy from a room and ventilation systems, which bring in fresh air in the house. The HVAC system has constraint on the timing that the room environment should reach the target temperature.

There are two types of air conditioners, non-inverter air conditioners and inverter air conditioners. Since the inverter air conditioners become popular due to their energy efficiency, we utilize a simple model of PID control to simulate the control of inverter air conditioners [**?**]. The amount $Q_a(t)$ of heat flow in a time unit (J/s) created by an air conditioner using PID control is calculated based on the following equation.

$$Q_a(t) = K_P e(t) + K_I \int_0^t e(\tau)d\tau + K_D \frac{de(t)}{dt} \quad (2)$$

Here, $e(t)$ is the difference between room temperature (T_{room}) and setting temperature($T_{setting}$). The parameters K_P, K_I, and K_D are the coefficients for the proportional, integral, and derivative terms of PID control and are estimated based on training data. Electrical energy consumed by air conditioner are calculated by the following equation.

$$E_a(t) = \frac{1}{COP} Q_a(t) \quad (3)$$

where COP is the coefficient of performance of the air conditioner.

Since the amount of ventilation heat flowing into a room depends on the amount of ventilation air, the specific heat of the air and the difference between outside temperature and indoor temperature, we consider that the amount of ventilation heat flow created by a ventilation fan can be modeled by the following equation.

$$Q_v(t) = \rho V_a C_a (T_{air}(t) - T_{room}(t)) \quad (4)$$

where $Q_v(t)$ is the amount of heat entering the room due to air ventilation per a time unit(J/s), ρ is the density of the air (kg/m^3), V_a is the air flow rate of the ventilation system (m^3/s), C_a is the specific heat of the air $(J/kg.K)$, $T_{air}(t)$ and $T_{room}(t)$ are the temperature of outside air and the room at the time t. The air flow rate can be controlled between different levels. Electrical energy consumed by a ventilation system (J/s) is calculated based on the air flow rate as the following equation.

$$E_v(t) = \alpha_v V_a(t) \quad (5)$$

where α_v is a coefficient of the ventilation system.

In this paper, we consider a control scenario in which a user is on the way back home and he will arrive home after a time period. His scheduler sends a command to the HVAC system of his house. The HVAC system must regulate room temperature to reach a desired range of temperature when the use comes back home.

It is difficult to precisely predict the change of room temperature and the energy consumption of a HVAC system for a long time period since they depends on various environment parameters such as outside temperature, outside humidity, solar radiation which are difficult to predict for a long time period. However, these environment parameters do not change much for a short-time period. Therefore, we propose a MPC control mechanism with short time prediction horizon to ensure the accuracy of prediction results. Furthermore, our MPC control mechanism only manipulates the setting points of a HVAC system such as the setting temperature of air conditioners and the air flow rate of ventilation fans. Hence, it is easy to implement in residential houses.

4.2. MPC control strategy

The purpose of our control algorithm is to minimize the amount of electrical energy consumption of the system while maintaining the room temperature within a desired temperature range during a desired time period. For example in a summer day, outside temperature may be lower than room temperature. When the difference is large, natural or mechanical ventilation should be used since it can reduce the room temperature with little electrical energy. However, when the difference is small, air conditioner should be used since the energy efficiency of air ventilation becomes small.

Our idea of applying MPC control strategies for the optimization of HVAC system operation is shown in Fig. 3. When a MPC controller receives a request message containing the desired time period from its user, it divides the operation period starting from the request receiving time until the end of the desired time period into a number of control steps. In one control step, a command set (i.e. the set points of the HVAC system) is kept unchanged.

We need to find out the command set, which can optimize the operation of the HVAC system. In order to do that, the MPC controller of a house receives sensor data at the beginning of a control step and sends the data to the thermal simulator to update the present environment status of the house. It then calculates all possibilities of command sets within the prediction period started from the beginning of the control step and send each of setting points to the thermal simulator. The thermal simulator will calculate the change of room temperature and energy consumption based on each command set. Here, environmental parameters, e.g. outside temperature, solar radiation, are supposed to be unchanged during the prediction period.

The MPC controller selects the command set which gives the best performance and send the control commands corresponding to the present control step to the HVAC system. After the HVAC system actually interacts with the thermal environment under the sent control commands, the MPC controller repeats the previous operations for the next control step.

The prediction horizon for MPC control scheme may be one control step (Fig. 3 a) or several control steps (Fig. 3 b). If the prediction horizon is only one control step, the MPC controller can only optimize the system efficiency in that control step but not the whole operation period. If the prediction horizon is a large number of control steps, the computation cost will be high since the cost of performance evaluation of a HVAC system for one command set is high and the number of all possibilities of command sets that need to be evaluated is large. Further, long prediction horizon will make the error of prediction results increase since environmental variables such as outside temperature, outside humidity, solar radiation may change heavily within a long prediction period while their data remain unchanged during the simulation. Hence, the prediction horizon need to be selected carefully.

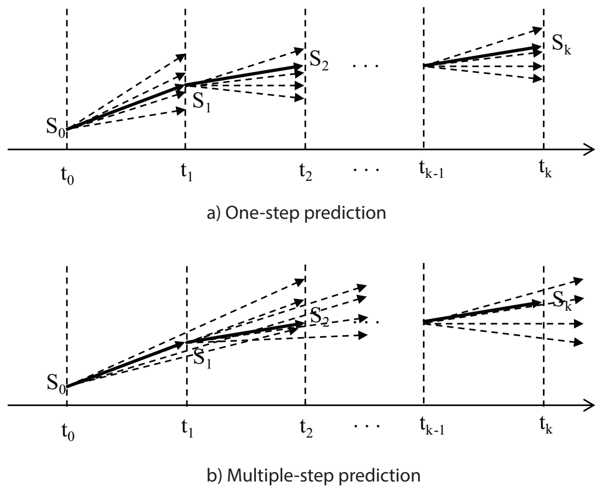

Figure 3. Selections of command sets for HVAC system.

4.3. Cost functions

Whenever the MPC controller sends a command set to the thermal simulation, the thermal simulation will return the prediction results of the change of room temperature and the amount of energy consumption within the prediction period. In order to select the best command set for HVAC system in each prediction period, we need a cost function which can evaluate the efficiency of HVAC system and thermal comfort based on prediction results.

Thermal comfort can be evaluated based on several parameters such as temperature, humidity, air velocity but the main factor is temperature [18]. In this research, for simplicity, we only use room temperature to evaluate thermal comfort. If the room temperature is outside the range of desired temperature, the user will feel uncomfortable. Therefore, we define a thermal discomfort index for a time period $[t_s, t_e]$ as follows.

$$U_{discomfort} = \int_{t_s}^{t_e} U(t)dt \tag{6}$$

where

$$U(t) = \begin{cases} 0 & \text{if } T_{room}(t) \in [T_{target}^{min}, T_{target}^{max}] \\ T_{room}(t) - T_{target}^{max} & \text{if } T_{room}(t) > T_{target}^{max} \\ T_{target}^{min} - T_{room}(t) & \text{if } T_{room}(t) < T_{target}^{min} \end{cases}$$

Here, $T_{room}(t)$ is the room temperature at the time t and $[T_{target}^{min}, T_{target}^{max}]$ is the range of predetermined user desired temperature.

In order to change the temperature of a room to the desired temperature range, a HVAC system consumes electrical energy to remove heat from the room in the case of cooling or add heat to the room in the case of heating. Thus, the efficiency of the HVAC is evaluated based on the amount of energy consumption E_{HVAC} and the amount of heat removed from or added to the room, which is calculated based on the room temperature at the beginning and at the end of the prediction period (T_s and T_e), as follows.

$$S = \begin{cases} C_v(T_{room}^{start} - T_{room}^{end}) - E_{HVAC} & \text{if cooling} \\ C_v(T_{room}^{end} - T_{room}^{start}) - E_{HVAC} & \text{if heating} \end{cases}$$

We consider that if the ending time of a prediction period is not within the desired time range, we should maximize the efficiency of the HVAC system. However, if the ending time of the prediction period is close to the beginning of the desired time range, we also need to consider the amount of heat Q_{target} that needs to be removed from the room in order for the room temperature to reach to the desired temperature range.

$$Q_{target} = \begin{cases} C_v(T_{room}^{end} - T_{target}^{max}) & \text{if cooling} \\ C_v(T_{target}^{min} - T_{room}^{end}) & \text{if heating} \end{cases}$$

The larger the heat amount Q_{target} is, the longer time the HVAC system must take to get the room temperature to reach to the desired temperature range. However, Q_{target} affects the temperature control target only when the operation time of HVAC system is not long enough to manipulate the room temperature. Therefore, if the ending time of the prediction period is not within the desired time period, we use the following cost function to select the best command set for HVAC system.

$$F_{cost} = S + \frac{1}{N_{step}Q_{target}} \tag{7}$$

where N_{step} is the number of control steps from the end time of the prediction period to the beginning time of the desired time period.

If the ending time of a prediction period is within the desired time period, we will select a command set, which minimizes thermal discomfort index. If there are multiple command sets that minimize thermal discomfort index, we will select the command set which consumes the minimum amount of energy consumption. Hence, the following cost function is used.

$$F_{cost} = (1 + U_{discomfort})(\Omega + E_{HVAC}) \tag{8}$$

Here, E_{HVAC} is the electrical energy consumed by the HVAC system in a prediction period, $U_{discomfort}$ is the thermal discomfort index for the prediction period, calculated by Eq. 6. Ω is a constant number, which is big enough to leverage the thermal discomfort index when E_{HVAC} is 0.

5. Evaluation

5.1. Evaluation environment

In order to verify the efficiency of our proposed method, we implement our control system in MATLAB/Simulink, which is a very powerful program to perform numerical and symbolic calculations, and is widely used in science and engineering.

Since the weather conditions are different

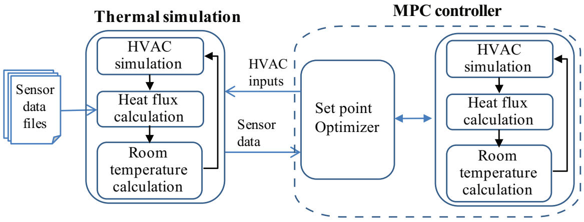

Figure 4. MPC control simulation.

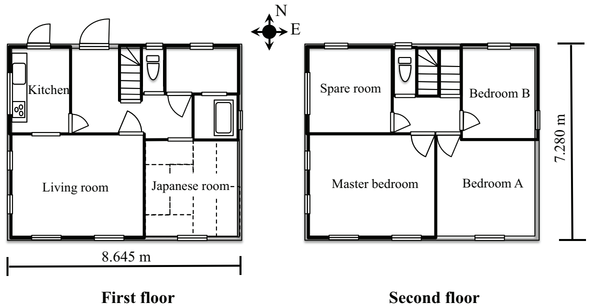

Figure 5. Structure of iHouse.

when performing each control scheme, we do not perform experiments but instead use simulation to evaluate the effectiveness of proposed control algorithm. As shown in Fig. 4, in each control step the thermal simulator reads sensor data at the the beginning time of the control step from file storage and sends sensor data to MPC controller, which calculates set points of HVAC systems for the control step and sends back the inputs to the thermal simulator. The thermal simulator then reads sensor data for the whole control step and perform simulation to calculate the change of room temperature and energy consumption of HVAC system in the control step. It then sends sensor data at the end of the control step as the sensor data at the beginning of the next control step and the simulation is repeated until the end of simulation.

We perform our simulation targeted on a real house called iHouse, which is a testbed for smart home services. The iHouse is located at Ishikawa prefecture, Japan. It is a typical 2-floor Japanese-style house, which can divide into 15 rooms. Appliances in iHouse such as air conditioners, wattmeters and sensors are connected to the network via ECHONET lite protocol [17]. Most of the rooms in the house

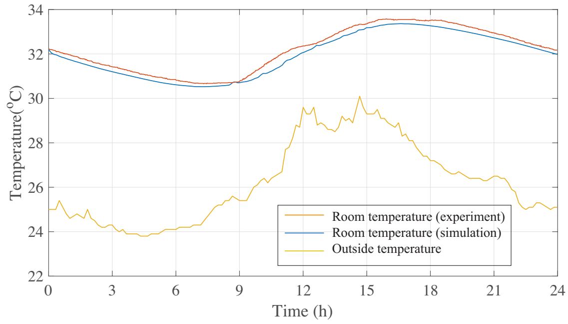

Figure 6. Room temperature and outdoor temperature during the experiment day.

Table 1. List of control commands for experimental HVAC system

Ventilation fan	
Control command	Operation
0	turn OFF
1	turn ON and $L_{speed} = 1$
2	turn ON and $L_{speed} = 2$
Air conditioner	
Control command	Operation
0	turn OFF
1	turn ON and $T_{setting} = T_{target}$
2	turn ON and $T_{setting} = T_{target} - 1$
3	turn ON and $T_{setting} = T_{target} - 2$

have one or more windows. The object of our verification is Bedroom A of the iHouse (Fig. 5).

The experiment day is 14th August 2012. The outside temperature and the temperature of Bedroom A of the iHouse without any operation of HVAC system during this day are shown in Fig. 6. The outside temperature is lower than the room temperature in all day. We perform thermal simulation for this day to confirm the accuracy of simulation results. As shown in Fig. 6, the mean deviation of simulation results is 0.23 degree centigrade. It means that our thermal simulator can achieve high accuracy.

In order to verify the efficiency of our proposed method, we perform three following control scenarios.

- Rule-based control mechanism: When receives the request, turns on the ventilation fan when the temperature of outside air is higher than room temperature. Turn off the

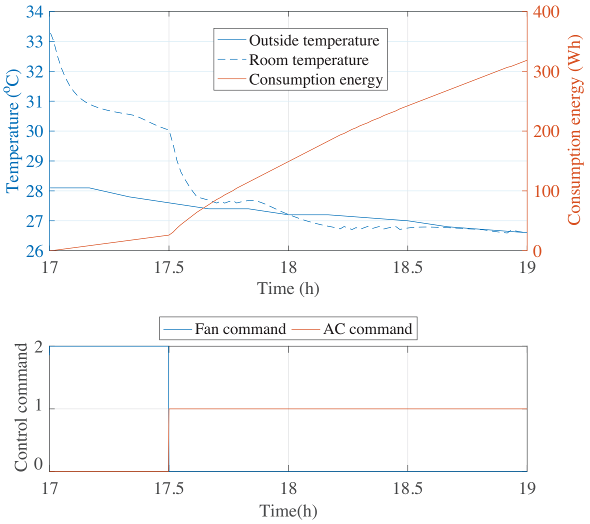

Figure 7. Results of rule-based control algorithm (temperature range: 26-27 degree).

Table 2. Simulation parameters of HVAC system

Parameter		**Value**
Control step		10 minutes
Room heat capacity		11224 J/K
Air conditioner		
- COP		3.05
Ventilation fan		
- Air flow	$L_{speed} = 1$	$0.097\ m^3/s$
	$L_{speed} = 2$	$0.146\ m^3/s$
- Electrical power	$L_{speed} = 1$	31 W
	$L_{speed} = 2$	53 W

ventilation fan and turn on the air conditioner 30 minutes before the target time

- Proposed MPC control mechanism

We simulate a HVAC system, which includes an inverted air conditioner and a ventilation fan in the room. We can set the setting temperature for the air conditioner and turn on/off the fan. Hence, the input command includes two parameters for ventilation fan and air conditioner. The operation corresponding to each control command is listed in Table 1. Simulation parameters are described in Table 2.

We consider an application scenario when a user is going to come back home. The user may send a notification message including his arrival time to the HVAC system. The HVAC system must control the room temperature to be within

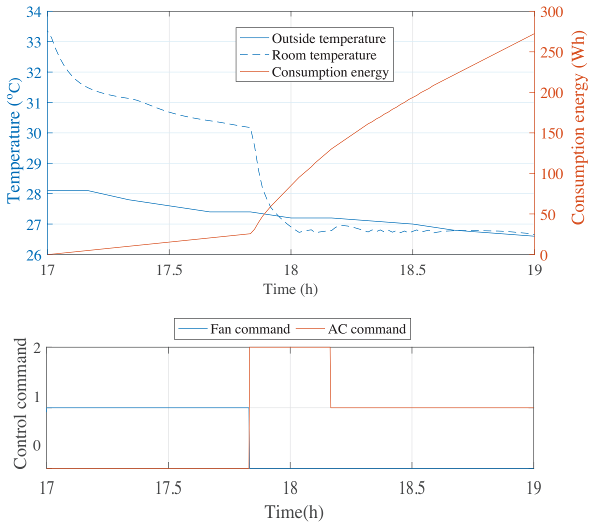

Figure 8. Results of MPC control algorithm (temperature range: 26-27 degree).

the desirable range right after his arrival time (i.e. the target time). In our simulation, the target time is 18:00 while the notification time of user arriving is 1 hour before the target time (i.e. 17:00). The simulation lasts until 19:00.

In order to find out the best solution of command control set of HVAC system in a prediction time period, we utilize a simple brute-force algorithm which searches all possibilities of control sets in a prediction time period. The number of control sets is proportional to the exponential of the number of control steps .

5.2. *Simulation results*

In the simulation of proposed MPC control scheme, we set the time duration of one control step to be 10 minutes. The prediction time is 20 minutes, twice as the time duration of a control step. We simulate two cases:

- The range of user desired temperature is set to [26°C-27°C].
- The range of user desired temperature is set to [25°C-26°C].

When the desired temperature range is set to [26°C-27°C], in rule-based method, the air conditioner is turned on at highest speed level

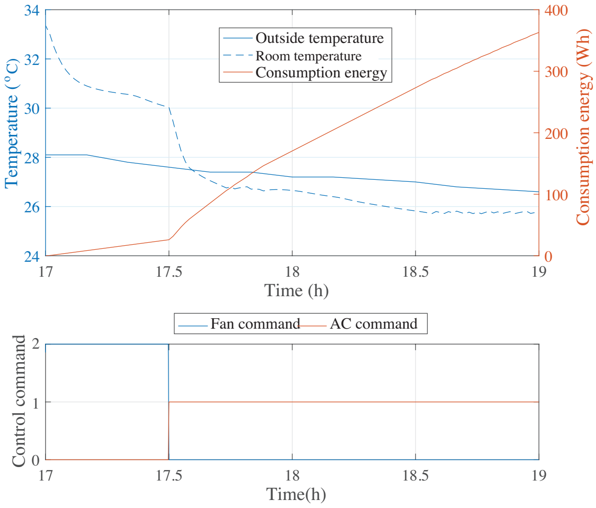

Figure 9. Results of rule-based control scheme (temperature range: 25-26 degree).

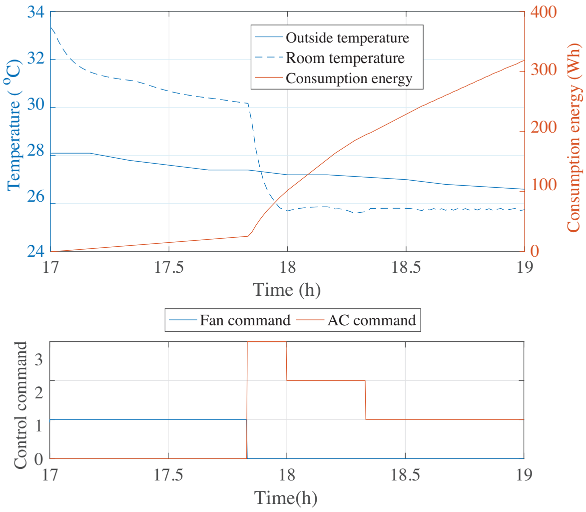

Figure 10. Results of MPC control scheme (temperature range: 25-25 degree).

30 minutes before the target time and the setting temperature is set to the target temperature (i.e. 27 degree centigrade). The simulation results (Fig. 7) show that the room temperature reach the desired temperature range at the target time while the amount of energy consumption is 318.53 Wh.

Proposed MPC control scheme (Fig. 8) turns on the ventilation fan at level 1 from 17:30 to 17:50. It then turns on the air conditioner with setting temperature of 26 degree centigrade from 17:50 to 18:10. It then sets the setting temperature of the air conditioner to be 27 degree centigrade. As the result, the room temperature reach the desired temperature range at the target time while the amount of energy consumption is 272.47 Wh, 14.4% lower than the energy consumption using rule-based control scheme.

When the desired temperature range is set to [25°C-26°C], in rule-based method, the room temperature cannot reach the desired temperature range at the target time (i.e. 18h00) and it only reaches the desired temperature range at 18h20 (Fig. 9). The amount of energy consumption is 368.1 Wh.

Proposed MPC control scheme (Fig. 10) turns on the ventilation fan at level 1 from 17:00 to 17:50. It then turns on the air conditioner with setting temperature of 24 degree centigrade from 17:50 to 18:00. The setting temperature of the

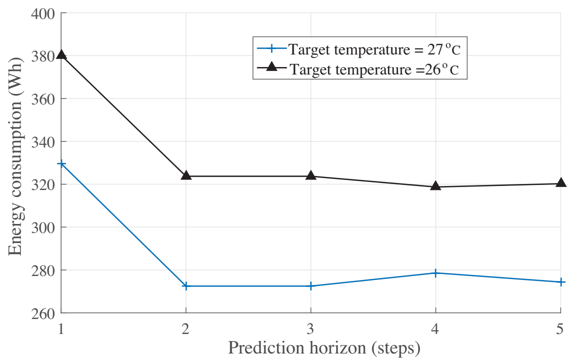

Figure 11. Results of energy consumption with the change of the prediction horizon.

air conditioner then changes to be 25 degree centigrade from 18:00 to 18:20 and changes to be 26 degree centigrade from 18:20 to 19:00. As the result, the room temperature reach the desired temperature range at the target time while the amount of energy consumption is 318.7 Wh, 13.4% lower than the energy consumption using rule-based control.

The evaluation results show that proposed MPC control scheme is more flexible and can achieve better energy efficiency with better user comfort comparing with rule-based control.

We change the prediction horizon which is multiple times of control step duration. As shown in Fig. 11, when the prediction horizon is only one control step, the energy consumption of

HVAC system is 14.85% more than when the prediction horizon is only two control steps. It is because the MPC controller only optimizes the system efficiency in one control step but not the whole operation period.However, the energy consumption of HVAC system only decreases little with the increase of the prediction time duration. Since the inaccuracy of prediction results may increases when the prediction horizon is long, the performance of the system even becomes worse in several cases. Further, when the prediction time duration is longer, the calculation cost for best solution of control command set is high since the size of searching space is proportional to the exponential of the control steps in one prediction time duration.

6. Conclusion

In this paper, we propose the utilization of our fitted thermal simulation to predict the change of room temperature and the amount of energy consumption of HVAC system. Our proposed MPC control scheme optimizes the control of HVAC system in a short prediction horizon based on a cost function, which can take into account both energy consumption and user thermal comfort. The evaluation results show that our system can achieve good performance comparing with rule-based control scheme.

In the future works, we will work on the improvement of calculation delay to realize realtime energy management for residential houses. We also apply MPC control mechanism for other devices such as heaters or curtains.

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References

[1] R. Rajkumar, I.L.I. Lee, L.S.L. Sha, J. Stankovic, Cyber-physical systems: The next computing revolution, in: Proceedings of the 47th Design Automation Conference. (2010) 731–736. https://doi.org/10.1145/1837274.1837461.

[2] M. Schmidt, C. Åhlund, Smart buildings as Cyber-Physical Systems: Data-driven predictive control strategies for energy efficiency, Renewable and Sustainable Energy Reviews. 90 (2018) 742–756. https://doi.org/10.1016/j.rser.2018.04.013.

[3] F. Oldewurtel, A. Parisio, C.N. Jones, D. Gyalistras, M. Gwerder, V. Stauch, B. Lehmann, M. Morari, Use of model predictive control and weather forecasts for energy efficient building climate control, Energy and Buildings. 45 (2012) 15–27. https://doi.org/10.1016/j.enbuild.2011.09.022.

[4] J. Hu, P. Karava, Model predictive control strategies for buildings with mixed-mode cooling, Building and Environment. 71 (2014) 233–244. https://doi.org/10.1016/j.buildenv.2013.09.005.

[5] Y. Kwak, J.H. Huh, C. Jang, Development of a model predictive control framework through real-time building energy management system data, Applied Energy. 155 (2015) 1–13. https://doi.org/10.1016/j.apenergy.2015.05.096.

[6] A. Afram, F. Janabi-Sharifi, Supervisory model predictive controller (MPC) for residential HVAC systems: Implementation and experimentation on archetype sustainable house in Toronto, Energy and Buildings. 154 (2017) 268–282. https://doi.org/10.1016/j.enbuild.2017.08.060.

[7] H. Nguyen, Y. Makino, A.O. Lim, Y. Tan, Y. Shinoda, Building high-accuracy thermal simulation for evaluation of thermal comfort in real houses, in: Lecture Notes in Computer Science, Vol. 7910 LNCS, Springer, Berlin, Heidelberg. 2013, pp. 159–166. https://doi.org/10.1007/978-3-642-39470-6-20.

[8] R. De Coninck, L. Helsen, Practical implementation and evaluation of model predictive control for an office building in Brussels, Energy and Buildings. 111 (2016) 290–298. https://doi.org/10.1016/j.enbuild.2015.11.014.

[9] D. Sturzenegger, D. Gyalistras, M. Morari, R.S. Smith, Model Predictive Climate Control of a Swiss Office Building: Implementation, Results, and Cost-Benefit Analysis, IEEE Transactions on Control Systems Technology. 24(1) (2016) 1–12. https://doi.org/10.1109/TCST.2015.2415411.

[10] F. Ascione, N. Bianco, C. De Stasio, G.M. Mauro,

G.P. Vanoli, Simulation-based model predictive control by the multi-objective optimization of building energy performance and thermal comfort, Energy and Buildings. 111 (2016) 131–144. https://doi.org/10.1016/j.enbuild.2015.11.033.

[11] J. Široký, F. Oldewurtel, J. Cigler, S. Prívara, Experimental analysis of model predictive control for an energy efficient building heating system, Applied Energy. 88(9) (2011) 3079–3087. https://doi.org/10.1016/j.apenergy.2011.03.009.

[12] James J. Hirsch, DOE-2 Building Energy Use and Cost Analysis Tool (2013). http://doe2.com/DOE2/index.html (accessed 24 October 2018)

[13] US Department of Energy, Energy Efficiency and Renewable Energy Office, Building Technology Program, EnergyPlus 8.9.0 (2018). https://energyplus.net (accessed 24 October 2018)

[14] Solar Energy Laboratory, TRNSYS 18: A Transient System Simulation Program, University of Wisconsin, Madison. http://sel.me.wisc.edu/trnsys (accessed 24 October 2018)

[15] M. Wallace, R. McBride, S. Aumi, P. Mhaskar, J. House, T. Salsbury, Energy efficient model predictive building temperature control, Chemical Engineering Science. 69(1) (2012) 45–58. https://doi.org/10.1016/j.ces.2011.07.023.

[16] O. Sian En, M. Yoshiki, Y. Lim, Y. Tan, Predictive thermal comfort control for cyber-physical home systems, in: Proceedings of 2018 13th Annual Conference on System of Systems Engineering (SoSE). (2018) 444–451. https://doi.org/10.1109/SYSOSE.2018.8428734.

[17] A.I. Dounis, C.Caraiscos, Advanced control systems engineering for energy and comfort management in a building environment—a review, Renewable and Sustainable Energy Reviews. 13(6-7) (2009) 1246–1261. https://doi.org/10.1016/j.rser.2008.09.015.

[18] P. Höppe, The physiological equivalent temperature - A universal index for the biometeorological assessment of the thermal environment, International Journal of Biometeorology. 43(2) (1999) 71–75. https://doi.org/10.1007/s004840050118.