Title	Predictive thermal comfort control for cyber-physical home systems
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Citation	2018 13th Annual Conference on System of Systems Engineering (SoSE): 444-451
Issue Date	2018-07
Type	Conference Paper
Text version	author
URL	http://hdl.handle.net/10119/15504
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Description	

Predictive Thermal Comfort Control for Cyber-Physical Home Systems

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***Abstract*—With the emergence of Internet of Things (IoT) and smart homes, the demand for energy efficient thermal comfort has also increased significantly to address the importance of quality of life (QoL) in a modern society. In this paper, we present a model predictive control (MPC) based thermal comfort controller for cyber-physical home systems (CPHS). The MPC controller is integrated into the existing Energy Efficient Thermal Comfort Control (EETCC) system that was developed for the experimental smart house, iHouse. The advantages of MPC was explored in a real time manner for reference tracking and energy minimization scenarios. Besides, Predicted Mean Vote (PMV) index is also adopted into the MPC controller to further enhance the energy efficiency and thermal comfort of the CPHS. The proposed methods are evaluated and verified under various seasons in a CPHS simulation using raw environmental data from the iHouse.**

***Index Terms*—Model Predictive Control, Cyber-Physical Systems, Smart Homes, Thermal Comfort**

I. Introduction

Digitally connected sensors and actuators are becoming a significant part of everyday life, thanks to the massive growth in the Internet of Things (IoT) market. It is projected that by the end of 2020, the number of IoT devices deployed globally will reach 212 billion [1]. While the potential of IoT applications are vast, there are certain applications that requires a deeper integration between the cyber and physical world. Such applications are often categorized under domain of cyber-physical systems (CPS). CPS often requires deep integration between sensing, computation, communication and control, which shares a lot of similarities with IoT. However, IoT differs slightly from CPS as IoT main focus is on the openness of the system while CPS focus toward closed-loop system. Smart home is one of the popular CPS applications, where recent increase in home automation efforts validates the growing importance on improving the quality of life (QoL) and energy efficiency, especially in residential and office buildings [2]–[5]. Besides, many key elements of a smart home coincides with the cores of CPS, thus rationalizing the need of CPS in smart homes.

Energy efficient thermal comfort is a part of smart home, where it provides cost effective comfort and convenience to its residents. Many researches have contributed to the advancement in this area, where details such as the architecture and envelop of the building, heating, ventilation and air conditioning (HVAC) devices and control are actively explored. Various thermal control methods have been investigated, from classical controls such as proportional integral derivative (PID) [3], [6] to modern control methods such as model predictive control (MPC) [7]–[11]. Many works also reported success with predictive algorithms in thermal comfort control, where its advantages far outweighs its disadvantages in general [12].

Thus, this paper presents a thermal comfort control system that explores the advantages of predictive control and methods to improve the energy efficiency without compromising the user well-being. The main goal for this paper is threefold: (i) to implement MPC based thermal comfort control for cyber-physical home systems (CPHS); and (ii) to implement real time control based on CPS approach; and (iii) to demonstrate the potential of thermal comfort index in enhancing energy efficiency.

The rest of the paper is organized as follows. Section 2 introduces the background on relevant topics to this paper. The experimental house and its system, plant modeling, PID and MPC controller details are described in Section 3. Proposed controllers are simulated under various seasons while its results and discussions are presented in Section 4. Finally, some relevant conclusions and future works are summarized in Section 5.

II. Background and Related Works

A. Smart Homes

Smart home is first used in 1984 by the American Association of House Builders, now known as the National Association of House Builders [13]. Smart home is defined in [14] as a home-like environment that incorporates ambient intelligence and automatic control that reacts to the behaviour of its occupants with various facilities. Home automation is commonly related with smart homes, which in fact they are similar [15]. Home automation involves automation of the home and household tasks with embedded system or computer to manipulate networked actuators and home appliances.

B. Cyber-Physical Home Systems

CPS is a system where its physical and computational resources are strictly interlinked together [5]. CPHS offers residents to live more comfortably, conveniently, cost effectively and more securely using CPS approach. A typical CPHS is illustrated in Fig. 1, where it is comprised of the cyber world, physical world and the communication network between them. The control domain, which includes data logging and supervisor controller are all part of the cyber world while the sensor domain and actuator domain are part of the physical world. Both cyber and physical world can be linked together by networks and communication protocols that are not limited to physical networks but also wireless networks.

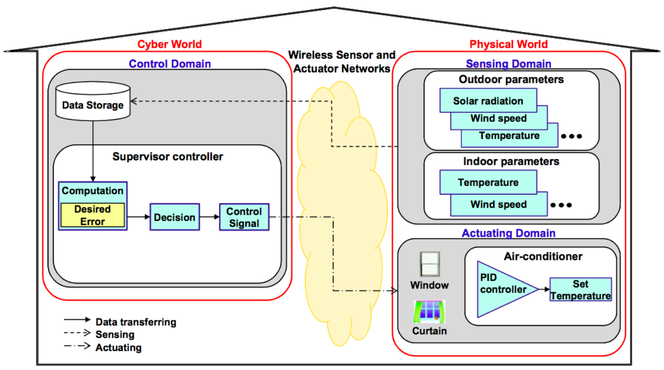

Fig. 1: Cyber-physical home system.

C. Energy Efficient Thermal Comfort

Thermal comfort is described as the state of the mind that expresses satisfaction with its thermal surrounding [5]. Conventionally, controllers often relies on air temperature feedback to regulate thermal level in indoor spaces. However, thermal comfort is much more than air temperature as it takes into account many other factors such as wind speed, humidity, metabolic rate, clothing insulation and radiant temperature [5]. Thermal comfort regulation does not only provides greater comfort but also the possibility of energy saving when compared to regulation of air temperature, thus the term energy efficient thermal comfort. One of the common thermal comfort index is the Predicted Mean Vote (PMV), which is described by a seven-point thermal sensation scale. Warm thermal sensations are represented by positive figures while cool sensations are represented by negative figures. PMV index is normally limited to occupants with metabolic rates between the range of 1.0 and $2.0\,\mathrm{met}$ and clothing thermal insulation that is rated $1.5\,\mathrm{clo}$ and below. Besides, for scenarios those air speed is more than $0.2\,\mathrm{m/s}$, the comfort zone would require adjustment based on Standard Effective Temperature (SET) model [18]. Some works that employs PMV index can be found in [4]–[9], [16], [17].

D. Related works

Researches in building thermal environment regulation are generally shifting from classical control to predictive algorithms such as MPC. One of the main factor of this trend is the straightforward implementation of the optimization problem, where multiple objectives and contraints can be included in the cost function. Other advantages of MPC compared to various controls are described in detail in [12]. Besides, some works that incorporates hybrid control method to regulate thermal environment can be found in [4], [5], [16], [17]. Most MPC thermal regulation simulation have large time step ranging from 1 to 3 hours [12]. Even the smallest time step for MPC thermal comfort simulation is 5 minutes [8], which does not take into account the real time aspect of CPS. Furthermore, most works on building thermal regulation are based on HVAC technologies such as variable air volume (VAV) [10], fan-coil [7], [8], water-based floor or ceiling heating [9], [11] while works on smart home with ductless air conditioner or split unit are almost non-existent.

Our previous efforts in application of CPHS involves multi actuator temperature control with PID [3], hybrid rule based algorithm for thermal comfort control with multi actuators [4] and the design and implementation of the Energy Efficient Thermal Comfort Control (EETCC) system in an actual experimental smart home [5]. The EETCC system with the hybrid rule based algorithm aims to promote energy efficiency by prioritizing the utilization of natural resource to maintain thermal comfort than using HVAC. Although the results were relatively successful, it is still a reactive controller by design that suffers from non-optimal control strategy as it senses and estimates deviations in thermal comfort level without foreseeing any future events. Thus, this paper is motivated to address the previous shortcomings by integrating predictive capability into the EETCC system. With the capability of foresight, the EETCC system should be able to compute optimal control strategies to further enhance energy efficiency and thermal comfort in CPHS.

III. Implementation Details

A. iHouse – Experimental Smart House

iHouse is an advanced experimental smart house, located at Nomi City, Ishikawa prefecture, Japan as showed in Fig. 2. It is a conventional two-floor Japanese-styled house featuring more than 300 sensors, home appliances, and electronic house devices that are connected using ECHONET Lite version 1.1 and ECHONET version 3.6.

Fig. 2: iHouse – experiment house of smart homes.

B. EETCC System Architecture

The work in this paper is based on the iHouse, where it incorporated various types of networked sensors and actuators that provides the necessary feedback parameters and output controls to the proposed thermal comfort controller. The relevant sensors and actuators are polled and controlled in real time over the network by the EETCC system designed in [5]. The EETCC system mainly provides two-way ECHONET Lite protocol translation, data processing while supporting real time device management and data logging. The EETCC system architecture is illustrated in Fig. 3, where it is comprised of three main components: (i) controller; (ii) communication protocol; and (iii) plant. This paper mainly focus on the controller and the plant in the EETCC system architecture.

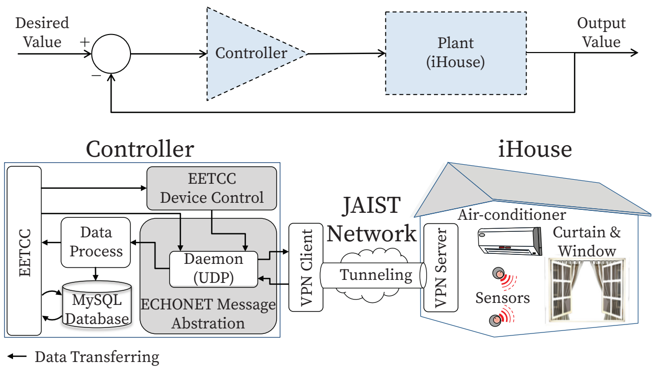

Fig. 3: EETCC system architecture.

C. Mathematical Representation

The plant that is modeled and simulated in this paper is the Bedroom A in the iHouse, where its thermodynamic characteristics can be modeled using heat equations. A high accuracy thermal simulation that is based on the iHouse Bedroom A is presented in [19] and its works are adapted to build the plant simulation model in this paper. First, the dynamic room temperature equation is given by

$$\frac{dT_{room}}{dt} = \frac{1}{C_{room}} \sum Q_{all} \tag{1}$$

where T_{room} is the temperature of the room in °C, C_{room} is the capacitance of the room given by the product of air density in $\mathrm{kg/m^3}$, volume of the room in $\mathrm{m^3}$, and specific heat capacity of air in kJ/kg°C. The summation of Q_{all} is comprised of the heat gain from HVAC, conduction and solar radiation through window and occupants in the room.

Besides, heat gain from the HVAC can be given by

$$Q_{aircond} = 1.08 \cdot CFM \cdot (T_{set} - T_{room}) \tag{2}$$

where CFM is the room volumetric airflow in $\mathrm{ft^3/min}$ and T_{set} is the setting temperature of HVAC in °C. Heat gain from conduction through window is given by

$$Q_{conduction} = u_w \cdot A_w \cdot (T_{out} - T_{room}) \tag{3}$$

where u_w is the u-value of a double glazing window, A_w is the surface area of a window in $\mathrm{m^2}$, and T_{out} is the outdoor temperature in °C. Heat gain from solar radiation through window is given by

$$Q_{solar} = q_{rad} \cdot A_w \cdot g_w \tag{4}$$

where q_{rad} is the measured solar radiation in $\mathrm{W/m^2}$ and g_w is the solar transmittance for the window. Heat gain from occupant sensible and latent heat in the room is given by

$$Q_{occu} = (n \cdot SHG \cdot CLF) + (n \cdot LHG) \tag{5}$$

where n is the number of occupant in the room, SHG is the sensible heat gain by each occupant, CLF is the cooling load factor for each occupant and LHG is the latent heat gain by each occupant.

Besides modeling using heat equations, the plant can also be modeled using RC (Resistance-Capacitance) approach as illustrated in Fig. 4. With this approach, the temperature of an element is similar to its voltage while outdoor environment temperature is similar to a voltage source that symbolize a constant temperature regardless of heat flow. A heat source such as HVAC can be described as a current source since electron flow can be used to symbolize heat flow. Thermal conductivity of a material such as double glazing glass windows can be described by an electrical resistor while the product of thermal capacitance and volume of an element is similar to electrical capacitance.

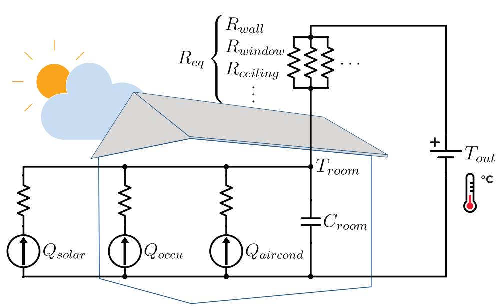

Fig. 4: Electrical model of room thermodynamic.

The heat equation based plant model can be transformed into a discrete state space model. A general state space model can be given by

$$x(k+1) = Ax(k) + Bu(k) + W\zeta(k) \tag{6}$$

$$y(k) = Cx(k) + \zeta(k) \tag{7}$$

where x is the system state vector, u is the system input vector, y is the system output vector while A, B, C and W are constant state-space matrices of coefficients. $\zeta(k)$ is the disturbance vector at interval k that is comprised of the heat gain from outdoor temperature, solar radiation and occupants in the room.

D. Proportional Integral Derivative

One of the most common used HVAC controller in industry is the PID controller due to its simplicity of implementation [20]. However, classical controller such as PID are often limited to linear and SISO systems. In order to circumvent the limitation of PID, a number of advanced approaches have been developed to regulate thermal comfort while taking into account of the non-linearity of the HVAC as noted in several works in [6], [16], [17]. Besides, previous works on multi actuators temperature control in the iHouse involved PID coupled with rule-based control (RBC) to enhance the energy efficiency of the system [3]. A general PID controller is used as the baseline controller in this paper, where it is given by

$$u(t) = K_p e(t) + K_i \int_0^t e(\tau)\, d\tau + K_d \frac{de(t)}{dt} \tag{8}$$

where K_p is the proportional gain, K_i is the integral gain, K_d is the derivative gain and $e(t)$ is the calculated error value at time t. By tuning the PID gain parameters, one is able to achieve good set point regulation at the expense of non-optimality.

E. Model Predictive Control

MPC applications for HVAC have increased throughout the years as a result of advancement in computing and networking technology [12]. Some of the main advantages of MPC includes the ability to cope with slow moving and long time delay applications, apply anticipated control strategies instead of corrective strategies and the ability to manage multiple objectives and constraints.

The section will discuss about MPC formulation, particularly on the optimization problem for various control strategies. The MPC system model that is simulated in this paper is illustrated in Fig. 5, where the plant is the iHouse Bedroom A that is subjected to disturbances from occupancy and outdoor environment. The MPC controller block is mainly comprised of the prediction block that is MPC internal estimated plant and the optimization block that performs control signal optimization with respect to the imposed cost function and constraints.

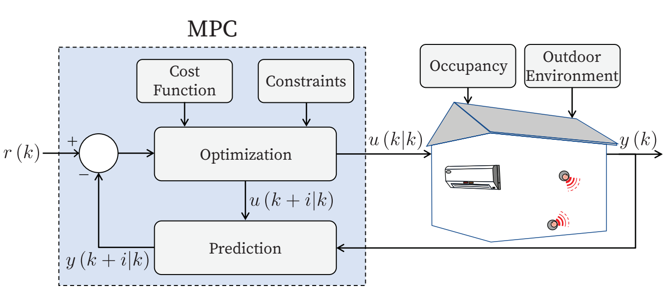

Fig. 5: MPC system model.

1) Reference Tracking (MPC 1): A general reference tracking optimization problem can be formulated where its cost function, J_k penalizes both the output deviation from the reference set point and the plant input control error can be given by

$$\begin{aligned} J_k = &\sum_{i=1}^{n_y} \left\{ w_i^y \left[r(k+1|k) - y(k+1|k) \right] \right\}^2 \\ &+ \sum_{i=0}^{n_u-1} \left\{ w_i^{\Delta u} \left[\Delta u(k+1|k) \right] \right\}^2 \\ \text{s.t.}& \\ &u_{min} \leq u(k+1|k) \leq u_{max} \end{aligned} \tag{9}$$

where n_y is the prediction horizon, n_u is the input horizon, w_i^y is the plant output tuning weight at ith prediction horizon step, $w_i^{\Delta u}$ is the change in plant input tuning weight at ith prediction horizon step, r is the reference signal, y is the predicted output and $\Delta u(k+1|k)$ is the change in the optimal plant input at time $k+i$ computed at interval k. Since every sensor and actuator have their performance limit, hence the cost function is also subjected to the actuator hard constraints. In this case, cost function is subjected to the HVAC minimum and maximum saturation points, which are u_{min} and u_{max} respectively.

2) Energy Minimization (MPC 2): This control strategy main objective is to minimize the energy consumption of HVAC while maintaining thermal comfort according to ASHRAE standards. The deviation of the reference signal and the predicted output is not penalized in this case, where the output tuning weight is set to zero. The PMV thermal comfort index minimum and maximum points, $y_{PMV,min}$ and $y_{PMV,max}$ are added to the cost function hard constraint together with the HVAC saturation points. Thus, a cost function that minimize the applied input control with the given constraints can be given by

$$\begin{aligned} J_k = &\sum_{i=1}^{n_u} \left\{ w_i^u \left[u(k+1|k) - u_{target}(k+i|k) \right] \right\}^2 \\ \text{s.t.}& \\ &u_{min} \leq u(k+1|k) \leq u_{max} \\ &y_{PMV,min} \leq y_{PMV}(k+1|k) \leq y_{PMV,max} \end{aligned} \tag{10}$$

where w_i^u is the plant input tuning weight at ith prediction horizon step and u_{target} is the target reference for the plant input. The plant input target reference can be represented by the availability of green energy, variable rate energy tariff or just a nominal value for energy consumption optimization. There are some related works [7], [21] that focused on the availability of green energy and economic based MPC for building thermal comfort control.

IV. Numerical Simulation

To evaluate the performance of MPC controller under various objectives and constraints, a four season simulation is conducted based on the plant modeled in the previous section. The outdoor temperature and solar radiation on 14th May 2013 (Spring), 15th August 2013 (Summer), 1st November

2013 (Autumn) and 1st February 2014 (Winter) is shown in Fig. 6, where each of the selected days represents a typical day with fair weather in their respective seasons. The remaining simulation parameters are listed in Table I.

TABLE I: Simulation parameters and settings.

Parameter	Value
Volume of room $(L \times W \times H)$, V_{room}	$5.005 \times 4.095 \times 2.4\,\mathrm{m}^3$
Density of air	$1.2\,\mathrm{kg/m}^3$
Specific heat capacity of air	$1.005\,\mathrm{kJ/kg°C}$
Air volume flow rate, CFM	$300\,\mathrm{ft}^3/\mathrm{min}$
Minimum cooling load of HVAC, u_{min}	$5\,\mathrm{kW}$
Maximum cooling load of HVAC, u_{max}	$6.3\,\mathrm{kW}$
Coefficient of performance, COP	3.44
Area of window type 1, A_{w1}	$1.815\,\mathrm{m}^2$
Area of window type 2, A_{w2}	$0.66\,\mathrm{m}^2$
U-value of window type 1, u_{w1}	$3.4\,\mathrm{W/m^2°C}$
U-value of window type 1, u_{w2}	$1.7\,\mathrm{W/m^2°C}$
Solar transmittance of window type 1, g_{w1}	0.79
Solar transmittance of window type 2, g_{w2}	0.41
Sensible heat gain by occupant, SHG	$0.09\,°\mathrm{C/W}$
Latent heat gain by occupant, LHG	$190\,\mathrm{Btu/h}$
Cooling load factor for occupant, CLF	1
Number of occupant, n	1
P of HVAC controller, K_p	9.387
I of HVAC controller, K_i	0.0875
D of HVAC controller, K_d	-38.854

Thermal comfort category B is chosen in this simulation as it represents an estimated value of 90% where the participants are satisfied with the thermal environment [18]. Nevertheless, the PMV thermal comfort range for each categories is tabulated in Table II.

TABLE II: Three categories of thermal comfort demands.

Category	PMV
A	$-0.2 \leq PMV \leq +0.2$
B	$-0.5 \leq PMV \leq +0.5$
C	$-0.7 \leq PMV \leq +0.7$

The simulation is built and simulated on Simulink platform to consider the real time aspect of the EETCC system, where it utilized outdoor environment data from the iHouse that are sampled every 10 second. Hence, the chosen time-step size for the simulation is also 10 second. Besides, the MPC sample time is also equal to the simulation time-step while its prediction and control horizon is configured to 2 minutes. This value is chosen after evaluating various prediction horizon for every season as shown in Fig. 7. In this case, longer prediction horizon does not guarantee the same returns in MPC performance as results from Fig. 7 exhibit characteristics of a quadratic curve. Thus, the local optimum found between prediction horizon of 60 seconds to 300 seconds is the global optimum. One of the factors that caused such phenomenon is the MPC internal model inaccuracy, where the longer the prediction horizon, the larger the summed up prediction error that is fed into MPC controller. Another distinct point in this simulation is that the chosen prediction horizon is very short when compared with most MPC implementations. This is due to the sampling time of most MPC implementation are generally about 1 hour which justified their long prediction time horizon between 5 to 48 hours [12].

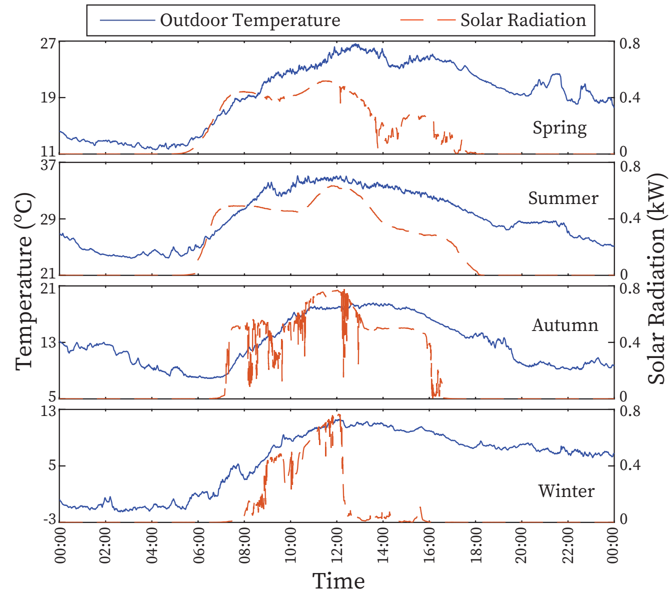

Fig. 6: Outdoor environment in various seasons.

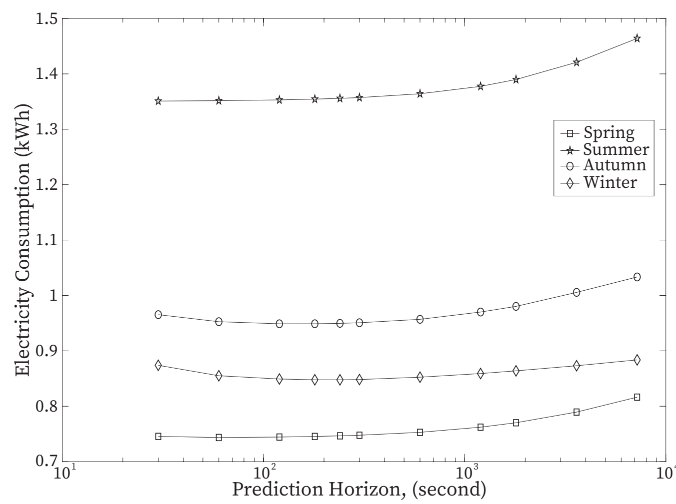

Fig. 7: Energy consumption of HVAC under various MPC prediction horizons and seasons.

A. Results and Discussion

In the previous section, two scenarios are introduced for the MPC controller: (i) reference tracking and (ii) energy minimization. The reference tracking performance of PID and MPC 1 controllers are compared and evaluated in the first scenario while the second scenario focused on difference between the input control strategies by MPC 1 and MPC 2 and the potential improvement in energy efficiency when PMV thermal comfort band is imposed as a constraint.

First, the step response of both PID and MPC 1 are simulated and the results are tabulated in Table III. The reference signal for both PID and MPC 1 is a constant value at $25\,^{\circ}\mathrm{C}$ throughout the simulation period. The rise time is defined in this paper is the time taken for controller response to increase from 10% of its steady-state value to 90% of output reference while settling time is defined as the time taken for the controller response reach and stay within 5% of the output reference signal. From the step response results, MPC 1 outperformed PID in closed-loop temperature regulation as both rise time and settling time for MPC 1 are lower while both controllers displayed no overshoot or undershoot. An example of the input control when step input is applied can be found from the control input plot for spring season in Fig. 8, where the initial input control from 00:00 to 01:00 (1 hour) is highlighted in the HVAC cooling and heating range from –2.5 to 2.5 kW. By observing the initial input control plot, it is clear that MPC 1 applied aggressive control strategies when compared to PID. This is caused by heavier penalty imposed on the reference tracking error of the output compared to the input control rate of change, which MPC 1 will compute the required cooling or heating power to decrease the output error in the shortest time without violating its pre-defined constraints. Hence, MPC 1 reference tracking performance is better than PID even under large disturbance.

TABLE III: Step response characteristics of PID and MPC 1.

Controller	Rise Time	Settling Time	Overshoot	Undershoot
PID	$208.89s$	$293.13s$	0	0
MPC 1	$114.80s$	$135.65s$	0	0

Most seasons except summer and during initialization state, the controllers utilized HVAC to heat up (positive control input) the plant to achieve its given reference value during night time while during daytime, the outdoor disturbances naturally increased the temperature in the plant by conduction, convection and radiation, hence HVAC is used to cool the plant (negative control input) as shown in Fig. 8 control input plots. Besides, the reference tracking performance after the controllers achieved steady state is also evaluated. It is observed that the reference tracking performance for both controllers are the best during spring season as the maximum deviation is $0.24\,^{\circ}\mathrm{C}$ and $0.028\,^{\circ}\mathrm{C}$ for PID and MPC 1 respectively. The worst reference tracking performance for both controllers occurred during autumn season, where the maximum deviation for PID and MPC 1 is $0.73\,^{\circ}\mathrm{C}$ and $0.072\,^{\circ}\mathrm{C}$ respectively. The effect of the outdoor disturbance is observed in the control input plot in Fig. 8, where significant fluctuation in both PID and MPC 1 control input is seen during autumn season. One of the main cause of this disturbance is the solar radiation during daytime (07:00 - 13:00) as shown in Fig. 6. Nevertheless, MPC 1 performed better than PID in metrics such as transient response, steady state response, reference tracking regulation and robustness to disturbances.

The second scenario is simulated under the same environmental conditions as the first scenario. This scenario introduced the MPC 2, which is subjected to the PMV thermal comfort band instead of reference tracking. As the PMV thermal comfort index considered six parameters to describe the occupant thermal comfort, it allowed a much relaxed operative temperature range when compared to PID and MPC 1. Hence, MPC 2 can take advantage of the PMV index to minimize the required control input which in turn reduces the energy consumption of the HVAC. This energy minimization effect is observed in Fig. 8, where MPC 2 computed and applied only the required control input to ensure that the plant PMV index value is within the given PMV upper and lower constraint (between grey boundary). Thus, if the initial PMV value is within the given PMV thermal comfort band, the MPC 2 will not apply any control input to allow the plant open loop response to run until the plant PMV value reached the upper or lower PMV boundary. This can be clearly observed during summer season room temperature, PMV and input control plot in Fig. 8 from 00:00 to 06:00. For seasons those outdoor temperatures are lower than the room temperature, MPC 2 would only apply the minimum required negative input control during the daytime and positive input control during the night time.

To evaluate the total electrical energy consumption of HVAC for each simulation scenarios, the total HVAC electricity consumption is computed from the equation

$$E_{aircond} = \frac{1}{COP} \int_{t_{start}}^{t_{end}} \left| Q_{aircond}\left(t\right) \right| dt \tag{11}$$

where COP is the coefficient of performance, t_{start} and t_{end} is the start and end time of the simulation. The total HVAC electricity consumption for PID, MPC 1 and MPC 2 is computed and plotted according to their respective seasons as shown in Fig. 9. For reference tracking scenario, the HVAC electricity consumption by MPC 1 is lower than PID by 1.053% (spring), 0.83% (autumn) and 0.90% (winter) respectively. However, the HVAC electricity consumption for MPC 1 is higher than PID by 0.66% during summer. MPC 1 applied aggressive control strategies that lead to lower settling time, tighter room temperature regulation and high initial electrical consumption. This may incur higher total electrical cost than PID as observed during summer season.

For the energy minimization scenario, MPC 2 managed to reduce the HVAC electricity consumption by 21.28% (spring), 11.76% (summer), 20.83% (autumn) and 22.73% (winter) when compared with MPC 1. This improvement in HVAC electricity consumption when PMV thermal comfort index is introduced over temperature reference tracking is consistent with other research finding [9].

There are several caveats regarding the simulated results in this paper, where future works can be performed to address their shortcomings. Firstly, the results from various seasons only represents the norminal performance or response from the proposed thermal comfort controllers during fair weather. A full year trend of PMV thermal comfort and HVAC energy consumption with MPC controller can be found in [9]. Besides, the scenarios presented in this paper also assumed

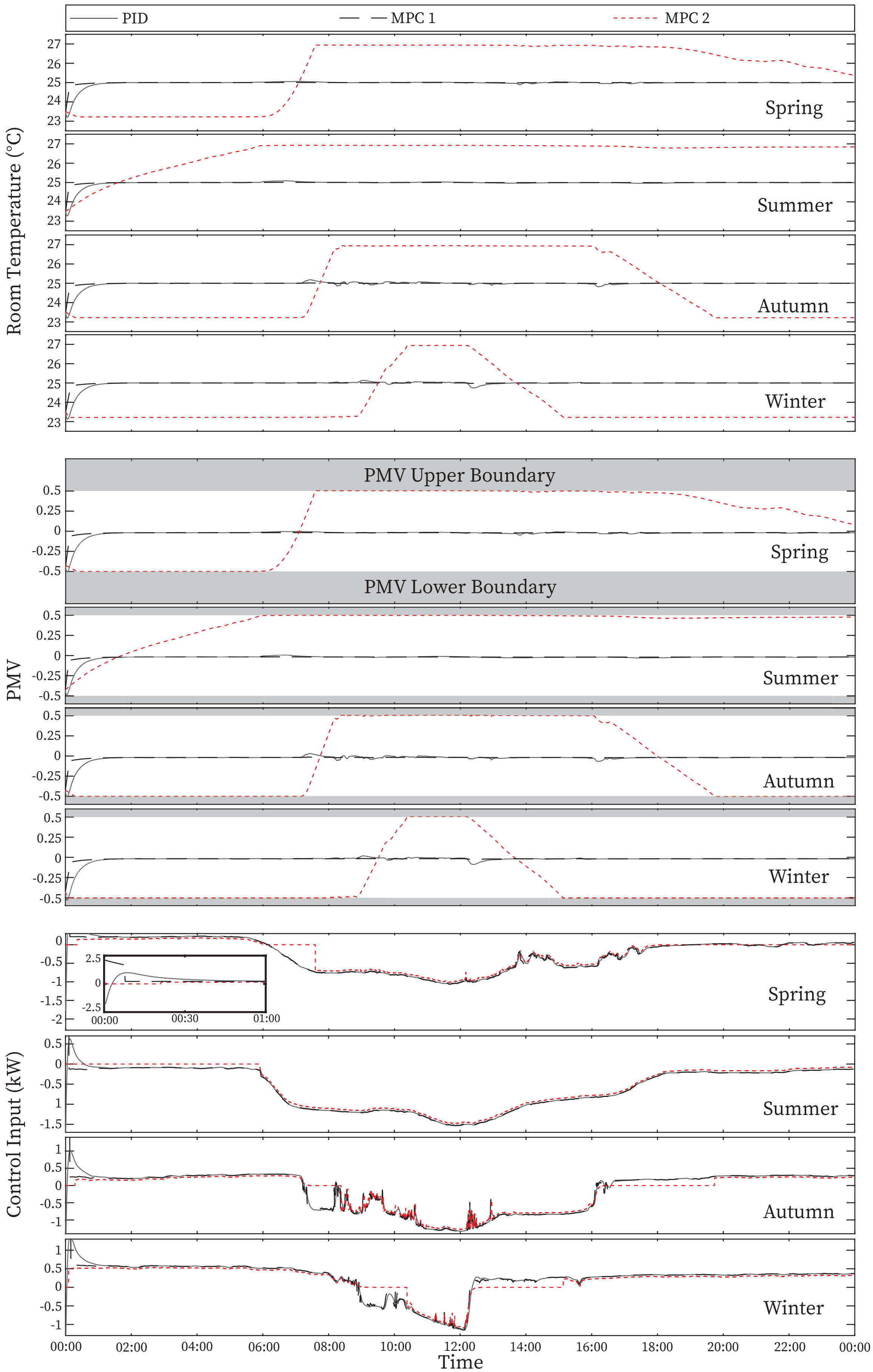

Fig. 8: Simulation results for all season.

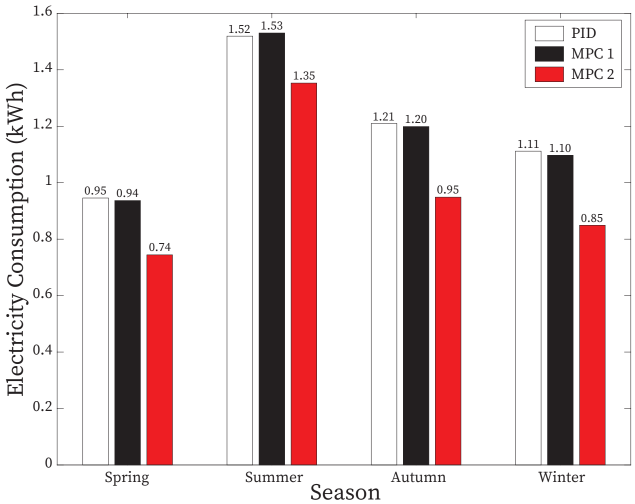

Fig. 9: Comparison between various controller energy consumptions for all seasons.

that the plant room temperature or thermal comfort have to be regulated throughout the simulation period. These scenarios might not be realistic in practise as the plant temperature or thermal comfort should only be regulated when the plant is occupied. Further energy reduction can be achieved by integrating occupancy detection and prediction to provide on-demand thermal comfort to the occupant. An example of such scheme is found in [22], where the MPC controller is integrated with occupant discomfort history and probabilistic occupancy prediction to provide energy efficient thermal comfort. Furthermore, preliminary modeling and simulation works have been performed based on the iHouse solar panel and fuel cell in [23]. This enables future works on integration of renewable energy into the EETCC system and MPC controller.

Concluding Remarks

This paper summarizes the implementation details of real time thermal comfort control with MPC in CPHS environment. Various MPC implementations are simulated and benchmarked against a PID controller to evaluate the performance and advantages of predictive capabilities in the domain of thermal comfort control. The four season simulations showed improvements in both temperature reference tracking and energy minimization scenarios when MPC is employed. Besides, an economic based MPC controller that takes into account the availability of green energy and electricity tariff as well as the occupancy will be explore in the future.

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