

2014

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Kim, Donghun; Witmer, Lucas; Brownson, Jeffrey R. S.; and Braun, James E., "Impact Of Solar Irradiance Data On MPC Performance Of Multizone Buildings" (2014). *International High Performance Buildings Conference*. Paper 158.
<http://docs.lib.purdue.edu/ihpbc/158>

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Impact of Solar Estimation on MPC Performance of Multizone Buildings

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ABSTRACT

Local solar irradiation data has been used for Model Predictive Control (MPC) in supervisory level building control systems, with significant influence demonstrated on perimeter building zones with a high fraction of window area. This work investigates the impact of uncertain solar estimation on MPC performance with respect to energy consumption and comfort by comparing MPC responses for a multi-zone building based on two solar data sources: measured local Plane of Array (POA) solar data and satellite Global Horizontal Irradiance (GHI) based modeled POA solar data. Hourly solar irradiation on tilted surfaces can be calculated from local or offsite GHI measurements by a common algorithm that includes an empirical correlation to decompose the beam and diffuse components, followed by the application of an anisotropic sky model. Real-time control decisions based on the modeled solar data have been found to violate comfort conditions within zones, particularly if off-site or satellite derived GHI data is employed. The presented case study results inform the value of information, revealing that MPC decisions based on satellite derived solar data cause comfort violations that depend strongly on the building system characteristics, such as HVAC and internal gains.

1. INTRODUCTION

Buildings are responsible for about 40% of the total primary energy use in the US (EIA, 2012). In the past three decades, various advanced control approaches have been studied to reduce energy consumption, particularly for large commercial buildings. One of the most popular and widely studied approaches is Model Predictive Control (MPC), in which an optimal control problem over a finite prediction horizon is solved at each sampling time using a system model. MPC is capable of reducing energy consumption, peak demand, and total energy costs, as shown by Prívvara et al. (2011); Ma et al. (2010); Braun (1990). The controller communicates with the Building Management System (BMS) where real-time measured data are stored. The control algorithm relies on forecasts of disturbances and a model which predicts future outputs based on predicted disturbances and candidate control inputs. The qualities of the model and of the disturbance information are crucial parts of MPC performance.

While an atypical data source for real-time building energy control, we show that solar irradiation data can be meaningfully used by Model Predictive Controllers, particularly for high window area ratio buildings. Solar irradiation on surfaces is typically calculated by a series of algorithms including an empirical correlation as specified in (Reindl et al., 1990) to separate irradiation components from Global Horizontal Irradiance (GHI). This data is occasionally incorporated in the broad set of “Weather Data”, but is not typically an input for real-time building controls, which ordinarily make predictive decisions based on outside air temperature. Even when incorporated into the meteorological data set, control decisions based on empirical correlation modeled solar data are likely wrong at certain times due to the difference between the modeled and measured

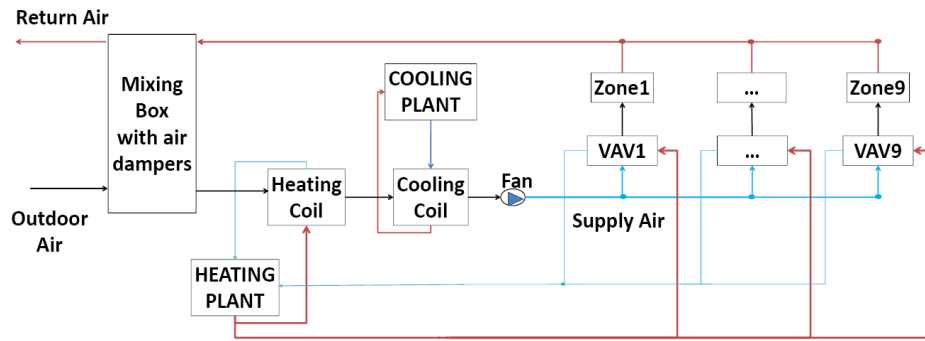


Figure 1: Schematic of the HVAC system

information (Gueymard, 2009; Burger et al., 2013). In this paper, the impacts on MPC performance on a multi-zone building with respect to energy consumption and comfort are studied for two different sources of solar irradiation data; satellite measured GHI transposed onto vertical surfaces and on-site measured irradiation on vertical surfaces. Locally measured GHI transposed onto vertical surfaces is anticipated to give results somewhere between the results found in this work and is part of ongoing work.

2. CASE STUDY

2.1 Building and HVAC Model

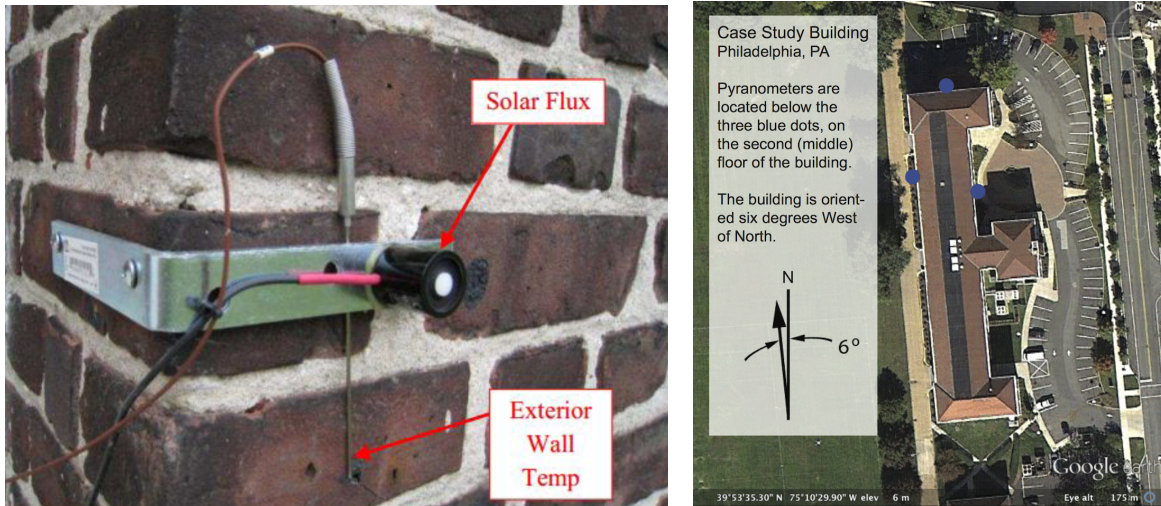
The case study building is located in Philadelphia, Pennsylvania, USA. The building contains three independent HVAC systems, one for each of the north, south, and middle wings of the building, respectively. Twenty geometric zones were modeled, with nine zones under the control of a mechanical ventilation system and the remaining eleven unconditioned (stairs, attics, etc.). As shown in Figure 1, the HVAC system consisted of one air handling unit (AHU), nine variable air volume terminal units (VAV boxes), a cooling plant, and a heating plant. Figure 5 shows an external view of the building. Characteristic features for the building energy model are listed below:

- 55,000 square feet of total floor area
- 3 occupied floors with basement and attic spaces for a total of 59 zones
- One Direct Expansion (DX) cooling coil serves the 9 thermal zones (9 VAV boxes), see Figure 1.
- Meteorological data for Philadelphia including TMY2, Weather Analytics AMY satellite based irradiance data, on-site weather station measurements, and on-site Plane of Array (POA) irradiance measurements.
- Building orientation is primarily on a North-South axis with a slight rotation of six degrees West of North, see Figure 2(b).

The DX coil has been modeled with experimental data. This MPC configuration minimizes HVAC energy costs in a fixed price scenario, which is the equivalent of the minimization of HVAC energy consumption. Therefore the DX coil characteristics critically impact the MPC analysis. The HVAC systems in the case study building have been summarized as well:

- DX coil compressor power consumption dominates fan power consumption; measured data during summer 2013 shows the supply fan takes around 10% to 30% of total HVAC power consumption.
- A higher supply air temperature set-point reduces energy consumption by decreasing the DX coil load, thereby decreasing the compressor power.

The system models used in this building energy model were developed and compared to models developed in TRNSYS (Klein et al., 2004) and in the Modelica Buildings Library (Wetter, 2009). The comparisons are provided in Kim et al. (2013). On-site solar irradiation Plane of Array (POA) measurements on



(a) Photograph of solar irradiance sensor (pyranometer) setup for vertical plane of array irradiation measurements.

(b) Aerial image of the case study building showing pyranometer locations and building orientation.

Figure 2: Images describing (a) solar irradiance sensor setup and (b) sensor locations with respect to building orientation.

vertical surfaces are taken with Licor LI200X pyranometers, as shown in Figure 2(a). Satellite derived solar irradiation estimates for GHI have been transposed to calculate POA irradiation through a series of steps including the (Reindl et al., 1990) diffuse fraction correlation and the (Perez et al., 1990) anisotropic sky model followed by a local shading filter developed in TRNSYS by (Witmer et al., 2013) to model local shading phenomena captured by the on-site sensors.

2.2 MPC assumptions for analysis and descriptions

Assumptions and implementation details were formed to provide a scenario where causal relationships to building response could be determined, eliminating factors other than the solar perturbations of interest. The assumptions were made purely for the purpose of a reduced order analysis, and it is understood that all assumptions may not be practical *in situ*. The assumptions include:

- MPC has a perfect building envelope and HVAC model, eliminating one source of model uncertainty, i.e. MPC controller has the same model for the HVAC/Envelope system in Figure 3.
- MPC is provided with a perfect forecast for internal gains and meteorology.
- Local controllers controlling VAV boxes are assumed to be perfect, i.e. local controllers track set-points perfectly.
- Perfect state estimation to run MPC controller. (A state observer such as Kalman filter is not used for analysis purposes.)

Equation 1 gives the following nonlinear optimization problem that is solved for the MPC. The MPC objective function minimizes energy cost subject to the constraints of a zone air temperature set-point range and capacities of the HVAC system, i.e. compressor stages and VAV damper positions.

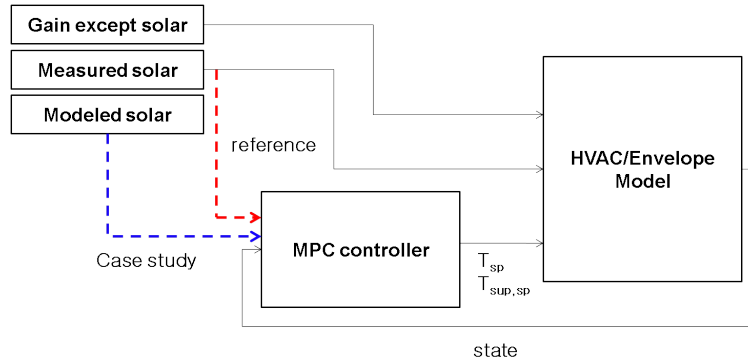


Figure 3: Distinction of the Two MPC responses, rMPC (red solid) and mMPC (blue dashed)

$$\begin{aligned}
 \min \quad & \sum_{k=1}^{N_p} R_k P(T_{z,sp}(k), T_{sup,sp}(k), Q_{load}(k), w(k)) \Delta t & (1) \\
 \text{s.t.} \quad & x(k+1) = Ax(k) + B_u T_{z,sp}(k) + B_w w(k) \\
 & Q_{load}(k) = Cx(k) + D_u T_{z,sp}(k) + D_w w(k) \\
 & f(P, T_{z,sp}, T_{sup,sp}, Q_{load}, w) = 0 \\
 & \underline{T}_{sp} \leq T_{sp}(k) \leq \bar{T}_{sp} \\
 & 1 \leq Stage(k) \leq 6 \\
 & 0.2 \leq m_{VAV,j}(k) \leq 1 & (2)
 \end{aligned}$$

Where:

R_k : Electricity rate

$T_{z,sp}$: Zone air temperature set-point

$T_{sup,sp}$: supply air temperature set-point

Q_{load} : Zonal thermal load

w : Disturbances including solar, outdoor air temperature, outdoor air humidity, internal heat/latent gains, etc.

$Stage$: DX coil compressor stages range from 1 to 6 for this case study

$m_{VAV,j}$: A normalized air flow rate for j^{th} zone; 0.2 and 1 correspond to a minimum and maximum damper position setting

A load model, in terms of $(A, B_u, B_w, C, D_u, D_w)$, for estimating zonal loads based on a candidate thermostat set-point and future disturbance information, is developed by inverting a building envelope model which has zone air temperatures as outputs and mechanical heat removal/addition rates as inputs. After the loads calculation, the model solves the HVAC equations, such as mass/energy balances and the fan/DX coil model, to calculate the total power consumption to meet the loads as a function of zone air temperature/humidity ratio, supply air temperature set-point, outdoor air temperature/humidity ratio and so on. Because the electricity rate is taken as constant, the objective function for the MPC is the minimization of HVAC energy consumption over a prediction horizon.

Before proceeding with the analysis, we argue an optimality condition of the multi-zone MPC solution: “At least one VAV damper must be fully opened to be optimal”. The proof is as follows: suppose the MPC decided a $T_{sup,sp}$, in which no VAV dampers are fully opened but the decision meets each zonal cooling load. Then

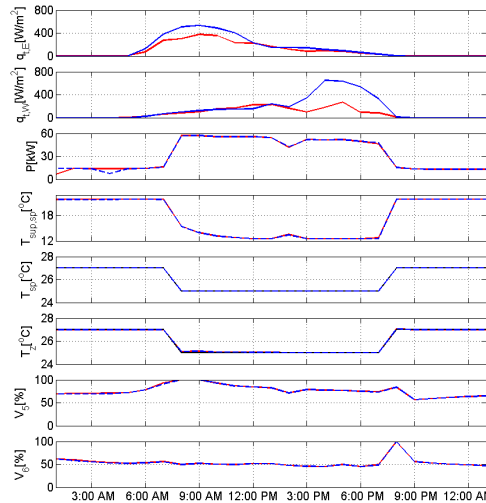


Figure 4: Comparisons of rMPC (red solid) and mMPC (blue dashed) for Case 0 (July 8, 2013)

there is an alternative decision to meet the loads by slightly opening all VAV dampers and increasing $T_{sup,sp}$, since all dampers are partially opened. Therefore, the alternative case will require more fan power but less compressor power (See at the end of Section 2.1). Because of cheaper fan power, it can be concluded that the alternative uses less HVAC energy compared to the MPC decision. This contradicts the optimality of the MPC.

Here we call the zone with a fully-opened damper the *critical zone*. This property is one of the most important parts for continuing the analysis. A reference MPC response, rMPC, is defined as follows; rMPC is informed by the on-site measured POA solar data which will have an effect on the building model. On the other hand, the MPC response informed by the modeled satellite based POA solar data, which differs from the on-site measured POA solar data acting on the system model, is named mMPC. See Figure 3 for a schematic of the difference between rMPC and mMPC. All other factors except the MPC informing solar information are the same for both MPCs.

3. RESULTS

As discussed, the POA solar information obtained from a satellite measurement based model may overestimate or underestimate the actual POA irradiance incident on a building façade. In order to understand the potential impact of solar information from varying sources, some reference days were selected from summer data where the solar model overestimates for the whole day (July 8, 2013) and where the model underestimates late in the day (July 11, 2013). Another reference day when both over and underestimation occurs was also selected (July 10, 2013). Before studying the potential impact for a long-prediction MPC, we start with a short-prediction MPC using a one hour prediction horizon. While the one hour prediction horizon does not capture typical load shifting that is evident with longer prediction horizons, the results are interesting given the assumption of a perfect forecast which increases in error with increasing prediction horizons. For this work, results from the reference on-site measured irradiance MPC response (rMPC) are marked with a solid red line while the MPC responses from the satellite based solar irradiation model (mMPC) are shown with a dashed blue line. The following abbreviations used in the resulting figures:

$q_{t,E}$: Total solar irradiation incident on the East surface

$q_{t,W}$: Total solar irradiation incident on the West surface

P : Total HVAC power consumption which is the sum of DX coil compressor power and supply fan power in this case study

$T_{sup,sp}$: Supply air temperature set-point decided by MPC

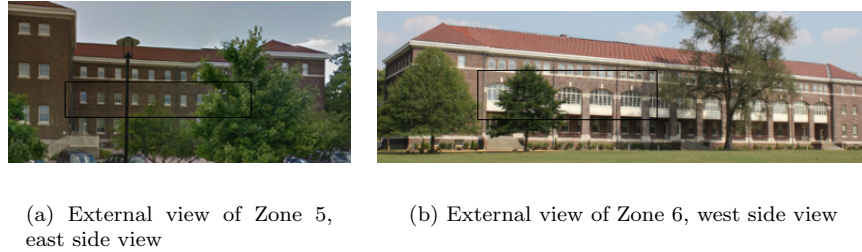


Figure 5: Zones of interests

T_{sp} : Zone air temperature set-point decided by MPC

T_z : Averaged zone air temperature

V_5 : Normalized air flow rate for the 2nd floor East office

3.1 Case 0: 1hr prediction MPC (July 8, 2013)

The responses (rMPC, mMPC) have been compared based on an assumed internal gain profile for each zone and the results are shown in Figure 4. As is shown, there are no significant differences in total HVAC energy consumption or peak power between rMPC and mMPC. Energy consumption and peak power for rMPC is (690.55 kWh/day, 57.13 kW) compared against (690.60 kWh/day, 57.16 kW) for mMPC. This case implies that incorrect solar disturbance information does not have any impact on MPC performance. However, it turns out that it is possible for a multi-zone building served by one AHU, as is this case, to have an impact. Consider a zone that is insensitive to solar, e.g. a zone on a ground floor in our case, but has an undersized VAV box. In order to meet the undersized zone's cooling load, the supply air has to be cooled further for peak times due to the lack of air flow capacity. Otherwise there is no way for the VAV local controller to track the zone temperature set-point with the undersized VAV box. The undersized zone is the *critical zone* defined above and is determining the MPC supply air temperature set-point.

Due to this lower supply air temperature, any other VAV controller has a potential capacity to meet their loads by adjusting their VAV damper positions. Therefore no comfort issues occur. Furthermore the critical zone is insensitive to solar and it *determines* the supply air temperature set-point to meet the zonal cooling load, the satellite derived solar information does not cause a significant difference on energy consumption between the two MPC.

To further study the impact of POA solar information, the critical zone needs to be changed to other zones that are sensitive to solar. In order to do that, internal gain profiles were changed for subsequent cases such that Zone 5 (East, 2nd floor) and Zone 6 (West, 2nd floor) in Figure 5 would be the critical zones.

3.2 Case 1: Overestimated solar irradiance with 1hr prediction MPC (July 8, 2013)

The red lines for the $q_{t,E}$ and $q_{t,W}$ plots in Figure 6 indicate measured POA values while the blue lines represent the satellite based modeled values. For Case 1, the solar model overestimates the on-site measured solar information for both East and West surfaces. From the T_{sp} plot (row 5 of Figure 6(a)), both rMPC and mMPC determine the thermostat set-points at the upper bound and is because the decrease of a thermostat set-point will lead to an increase of cooling loads for all zones.

At this moment, we will focus on the rMPC (red solid) in Figure 6(a). It can be checked that the VAV damper serving Zone 5 is fully opened from the V_5 -plot, i.e. it reaches its maximal air flow rate. Therefore Zone 5 is the *critical zone*, during occupied times for July 8, 2013, resulting in the expectation that mMPC will show different performances on this date. MPC performance must be sensitive to solar information since it affects the load directly and the supply air temperature set-point will be determined by the critical zone to meet the load.

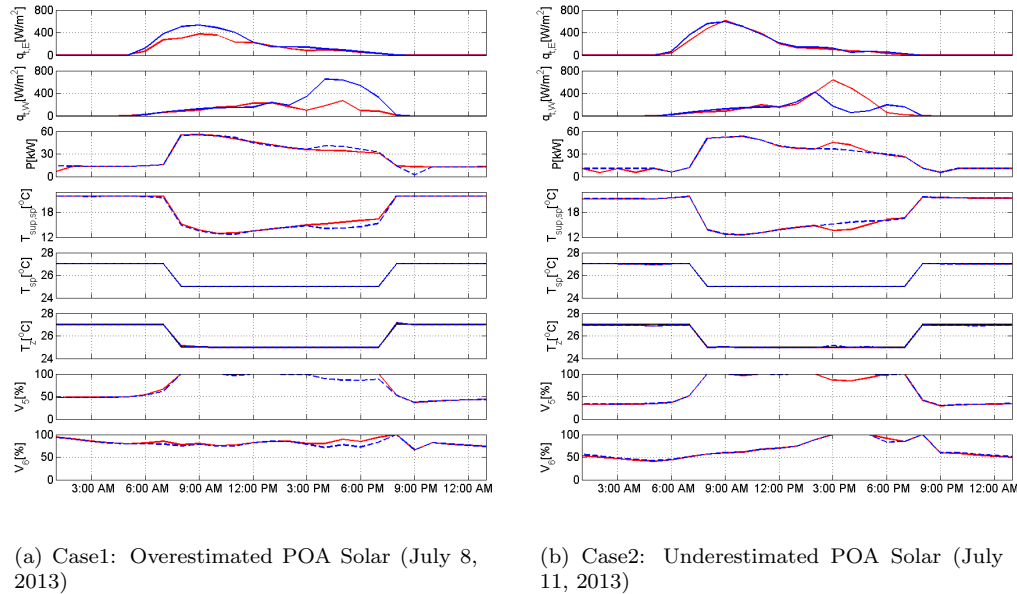


Figure 6: Comparisons of rMPC (red solid) and mMPC (blue dashed) for Case 1 and 2

Now let's look at the mMPC (blue dashed) responses in Figure 6(a). First, the mMPC will predict a higher cooling load than the rMPC due to the overestimation of the POA solar irradiation. This leads the mMPC to have a lower supply air temperature set-point in order to meet the higher load compared to rMPC (See $T_{sup,sp}$ plot, row 4 in Figure 6(a)). Therefore the mMPC results in an increase in energy consumption of about 4.6% compared to rMPC. However there is no comfort issue for the mMPC due to the lower supply air temperature which allows the local controller to meet the thermostat set-point (See V_5 and T_z plots).

3.3 Case 2: Underestimated solar irradiance with 1hr prediction MPC (July 11, 2013)

Overestimation is not always the case. July 11 is a case of underestimation, where the solar model underestimates the on-site measured POA solar information as shown in the $q_{t,W}$ plot in Figure 6(b). From the V_5 and V_6 plots, both zones are critical zones depending on time. Because the mMPC under-predicts the actual solar irradiance, the MPC decided a higher supply air temperature set-point assuming that it can meet the zone load with the duct air temperature (See the $T_{sup,sp}$ plot in Figure 6(b)). However the true cooling load is higher than predicted and the MPC decision for supply air is not cold enough. Therefore, there is no way for the local controllers to meet the true load resulting in the mMPC violating a comfort constraint as shown in the T_z plot in Figure 6(b). Because T_z is the 9-zone-averaged temperature, we extract the Zone 6 temperature. The peak value of the comfort violation is 2.69°C for the zone. Due to the higher supply air temperature set-point, mMPC takes 2.68% less energy consumption compared to rMPC at the cost of violating comfort requirements.

3.4 Case 3: Under/over solar irradiance with 1hr prediction MPC (July 10, 2013)

The analysis determined the following:

- Overestimation case: MPC results in higher energy cost with no comfort cost.
- Underestimation case: MPC has lower energy cost with increased comfort cost.

In Case 3, we confirm the arguments by selecting a day in which the solar model overestimates in the morning while it underestimates in the afternoon; July 10, 2013. The comparison between measured POA and calculated POA solar irradiation are shown in Figure 7. Due to the overestimation before noon, the

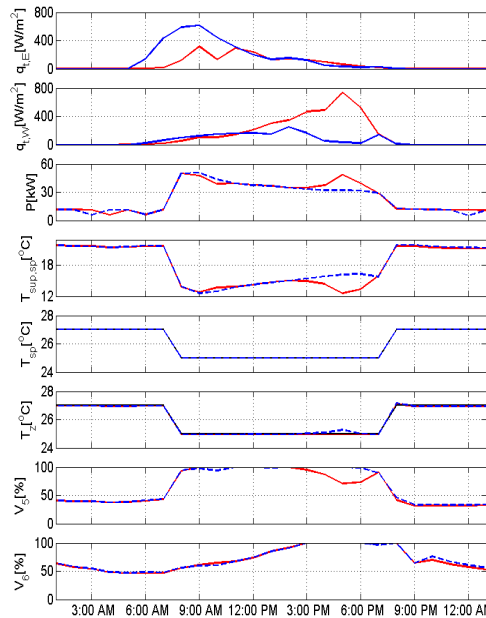


Figure 7: Comparisons of rMPC (red solid) and mMPC (blue dashed) for Case 3

mMPC tends to drop the supply air temperature set-point, causing higher energy consumption compared to the rMPC (See P plot in Figure 7). During the afternoon, the mMPC tends to increase the supply air temperature set-point because the cooling load is underestimated. Again, the same reasoning from Case 2 can be applied for the afternoon of this case.

3.5 Case 4: 5-hr prediction MPC

For a final case, the model is run with a 5-hr prediction horizon and comparisons are made between rMPC and mMPC. Compared to the one hour prediction MPCs, the use of the building's thermal mass is noticeable (See the T_{sp} plot in Figure 8). Since we assumed the electricity price is fixed, the driving force for the pre-cooling is purely due to DX coil performance, i.e. high sensible COP at a part load condition and for low outside temperature. From July 8 to July 10, the mMPC pre-cools the building more actively than rMPC. This is attributed to the over-prediction POA solar shown in the $q_{t,E}$ and T_{sp} plots in Figure 8. For July 12, the opposite case can be seen. During the afternoon, comfort violation occurs whenever the solar model underestimates. One interesting point is that overall energy consumption of mMPC is only 0.43% higher than rMPC. This is due to the unbiased nature of the solar model. Therefore the only different thing is a comfort violation of mMPC when the solar model underestimates.

As a final assessment of the impact of solar information on MPC cooling loads, the entire month of July was simulated and the results are summarized in Table 1. For the case of conventional, $T_{sup,sp}$ is fixed to 14° and $T_{z,sp}$ is schedule to the comfort upper bound. MPCs achieved around 12% energy savings compare to the conventional case. For the simulation period, the fixed supply air temperature set-point was not enough to meet a cooling load for a zone for a peak day, thereby it shows poorest comfort. The mMPC requires 0.25% less energy which is deemed insignificant, while comfort violation is significant. The worst day for the comfort violation occurs for a 4 hour period with a peak value of 2.93°C and the time average violation of about 1°C .

4. CONCLUSIONS

In this paper, the impact of solar irradiation data on Model Predictive Control has been analyzed for a multi-zone building served by one air handling unit and provides clear insight. Important findings specific

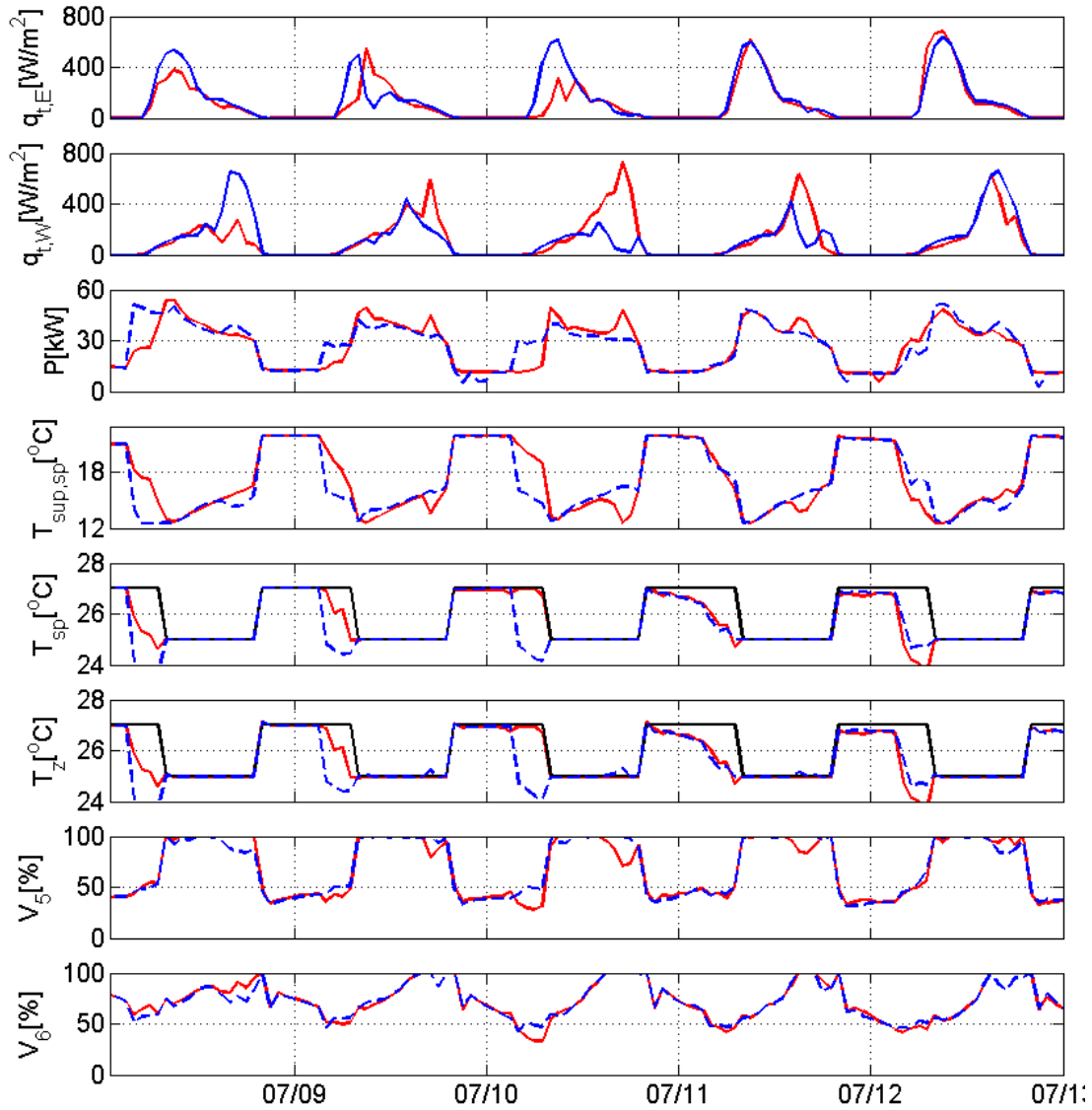


Figure 8: Comparisons of rMPC (red solid) and mMPC (blue dashed) for Case 4

Table 1: Comparisons of 5-hr rMPC and mMPC for a one month cooling simulation period.

	Energy consumption [kWh/day]	Peak comfort violation
Conventional	719.31	3.17°C
rMPC	628.63	.
mMPC	627.05	2.93°C

to the case study have been summarized:

- When a critical zone is sensitive to solar, MPC with modeled solar compared to MPC using local solar measurements causes higher energy cost but has no comfort cost for the overestimation case and causes less energy cost but increases comfort cost for the underestimation case.
- Because the solar transposition model overestimates for some times and underestimates for other times quite randomly energy consumption between the reference MPC and the MPC with imperfect information of solar is negligible while comfort violations are a significant issue.
- When a critical zone is not sensitive to solar irradiation, the choice of using local measured solar or modeled solar does not have a significant effect on the MPC despite other zones being conditioned that are sensitive to solar loads.

The degree of comfort violation is dependent on not only the building envelope, e.g. window area ratio, but also is dependent on the HVAC equipment, e.g. size of the VAV, and internal gain profiles. For high percentage window area buildings (DOE BTO Commercial Reference Medium Office 60%, compared with this case study building at about 30%), the comfort issue will be more significant. While this study focuses on solar loads, a similar analysis can be applied for load estimation/prediction error.

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ACKNOWLEDGEMENTS

This work was supported by the U.S. Department of Energy’s Consortium for Building Energy Innovation under award number DE-EE0004261.