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Stochastic model predictive control of mixed-mode buildings based on probabilistic interactions of occupants with window blinds

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ABSTRACT

The paper presents a stochastic model predictive control (SMPC) framework for buildings with mixed-mode cooling and demonstrates a comparison with deterministic model predictive control (DMPC) and standard heuristic rules. In this study, a probabilistic model of occupants' behavior on window blind closing event is used to represent the stochastic disturbance acting on the system over the prediction horizon. Monte Carlo (MC) simulation was used to capture this stochastic effect. It was found that SMPC leads to higher amount of energy consumption, providing a more realistic evaluation for the performance bounds of predictive control in mixed-mode buildings since it considers the occupant-building interactions. Also it was found that SMPC results in lower thermal comfort violations than DMPC and significantly lower compared to heuristic control.

1. INTRODUCTION

As high performance design standards of buildings evolve to more effectively exploit on-site renewable energy sources, buildings' energy and environmental performance becomes more sensitive to the presence, activities, and interaction of occupants with building comfort delivery systems that affect the buildings' energy balance (Torcellini, 2004). If we are to attempt to optimize the design of future high performance buildings and better match their demands for energy with that supplied from local generation and storage capacity, it will be necessary to consider the stochastic nature of their occupants. To do that, we will have to move from deterministic design and control into a new stochastic framework, where occupant disturbances on the actual system can be accounted for. In this context, the main benefits of stochastic models are to help to quantitatively estimate the uncertainties of the parameters of interest or more generally their distributions.

Occupants create disturbances to building models through the following two actions:

- Occupants' presence/absence which can make a difference in desired set points (air temperature, ventilation rate, illuminance, windows opening schedule etc.) Presence/absence of occupants is usually denoted by occupancy schedules.
- Occupant's interaction with the building (e.g. how to open manual operable windows, how to control manual blinds, working with appliances which results in different internal load profiles etc.)

In the current practice, building energy management systems mostly use presence/absence information for control strategies and consider constant values for the effect of occupants' activities such as internal gains, according to occupancy schedule which is being used. The method which is mostly used by simulation tools to represent occupancy is the so-called schedule diversity profile or diversity factors (Davis and Nutter, 2010). Using this deterministic approach has the advantage of model simplicity but it comes with the assumption of representing human behavior just by repeating standard patterns of occupant presence/absence and occupants' interaction with building systems such as lights and appliances. These assumptions may lead to considerable errors in predictions of the load profiles and peak demand in resources of a building, which in turn will influence the choice and sizing of the equipment at design stage or control decisions at the stage of building operation. The reason is that through this method, the average impact of internal heat gains (from occupant, lighting and equipment) on energy consumption and cooling load of the building is just estimation and cannot represent the stochastic variations of occupancy in time and space. In addition, the datasets corresponding to occupancy schedule in its all stochastic variety from survey and measurement are still scarce, and even if such datasets were available, since occupancy may vary extensively from one building to another depending on the type, size and use of the building, they may not represent actual occupancy precisely.

Therefore, various research studies have been conducted to derive more accurate models for occupancy schedules and occupants' interactions with building systems (Oldewurtel et al., 2013; Harle and Hopper, 2008; Chen et al., 2009; Newsham and Birt, 2010; Hay and Rice, 2009; Page et al., 2008; Haldi and Robinson, 2009; Rijal et al., 2011; Mozer, 1998). These models can be classified in two main categories:

- Pattern-prediction models. These models are developed based on a statistic experimental datasets and they are able to predict occupants' action patterns in both aspect of presence/absence and interactions.
- Real-time models. These models output the state of occupancy or occupants' interactions in the real time and are usually based on sensor networks and interfaces installed in the building.

Specific differences between pattern-prediction and real-time models of occupants' disturbances imply that the former are certain to be more advantageous. As the first difference, real-time models are only used where the system response to state changes is instantaneous. That is why application of these models can be seen more in detection of occupants' presence/absence and lighting controls. Based on long-term monitoring of data and statistical methods, pattern-prediction models are able to predict actions with longer associated time responses as well. For example, response of temperature control to changes in building states and demands is much longer than lighting control. Therefore, in order to control HVAC systems, pattern-prediction models are much more suitable than real-time methods.

Second difference would be the usability of models for different buildings. Real-time models need the sensor network deployed and configured for each and every building while pattern-prediction models can be used for different buildings once the model is embedded in a building controller. They may also be used as an initial model and then fine-tuned during the actual building operation with monitored data from fewer sensors. Another significant difference is that unlike the real-time models, pattern-prediction models can be used during the building design stage. This is an important feature which enables the designer to investigate the interactions between design and control variables.

During the building operation, real-time models usually undergo a learning process during which a history of most recent actions of occupants is stored and analyzed to make the prediction of future states available (Mozer, 1998). This learning procedure at some point is similar to the long-term data monitoring in pattern-prediction models but it won't get started before the building is built and ready to start operating. That is, the learning process cannot be useful at building design phase or cannot be generalized to other buildings. Overall, it can be stated that although real-time models show promising results (Jazizadeh, 2013) through their participatory sensing using sensors, interfaces and learning algorithms (e.g., smart thermostats), such models are only viable for existing buildings and are more suitable for responsive, not predictive, control strategies.

In the current literature, implementation of occupants' behavior prediction models into building automation systems is getting considerable attention. Due to the randomness involved in their structure, stochastic models are usually computationally expensive (Tanner, 2013). Therefore, it is important to find the most efficient way of modeling to account for uncertainties coming from occupants. For modeling occupant-building interactions, randomness can be addressed by a Markov policy. This process can be characterized by a state space, a transition matrix describing the probabilities of particular transitions, and an initial state or initial distribution across the state space. Monte Carlo (MC) sampling technique is another approach that can secure a representative distribution of results when stochastic models are employed in simulation. If number of stochastic models involved and their level of randomness is higher, it is possible for MC simulation to become computationally expensive (Tanner, 2013). In the present work, since only one stochastic model of occupants was implemented and an efficient optimization algorithm was used (Hu and Karava, 2014b), we were able to use MC simulation with no concern about expensive computations.

In this study, a pattern-prediction model which is a probabilistic model of occupants' behavior on window blind closing event has been used along with application of MC simulation to develop a stochastic model predictive control (SMPC) framework for buildings with mixed-mode cooling. This paper extends previous work focused on the investigation of the performance bounds of deterministic model-based predictive control (Hu and Karava, 2014a; Hu and Karava, 2014b) by evaluating the potential performance benefits of DMPC.

2. MODEL DESCRIPTION

A two-zone lab building with mixed-mode cooling and high solar gains is considered as a test-bed. In the MPC formulation, the window opening schedule is optimized for the upcoming prediction horizon and the cost function is the minimization of energy usage subject to thermal comfort constraints. Optimal control sequences based on the proposed stochastic MPC framework will be compared with deterministic MPC approaches to investigate the impact of uncertainty due to occupant actions on window blinds. The dynamic model of the building and the probabilistic model of window blind usage is described first followed by the formulation of the model predictive controllers.

2.1 Test Building

A test-building, located at the Architectural Engineering Laboratories of Purdue University, with mixed-mode operation schemes, depicted in Figure 1 is the basis for the investigation in this study (Hu and Karava, 2014b). The building has a south (4.8 m × 4.6 m × 3.7 m) and a north (3.3 m × 4.6 m × 3.7 m) facing zone separated by an internal wall with a door opening. The south zone has a highly glazed façade (3.2 m × 3.2 m curtain-wall construction) facing west which has three sections: operable awning windows at the top (0.4 m × 3.0 m), hopper windows at the bottom (0.4 m × 3.0 m), and a middle section (2.2 m × 3.0 m) with no operable elements. Roller shades with transmittance of 6.4% are installed on the middle section. The north zone has an east-facing single casement window (1.5 m × 0.9 m). All windows are controlled independently by automatic actuators (FFI Inc.) receiving open/close control sequences from the building automation system. Mechanical cooling/heating is supplied by a split-type air conditioner with the indoor unit installed in the south zone. An exhaust fan is installed to draw air from the south zone (when needed) to strengthen the airflow into the building. The envelope, floor and ceiling is well insulated with R-value of 20 (3.52 ºC•m2/W) and the concrete floor slab is 0.1 m thick providing a significant amount of cooling storage capacity. The internal door can be open or closed (and sealed) to allow testing of multiple models of operation. The present study is focused on a private office room so the internal door is assumed to be closed to represent a single-zone case (south zone). It is also assumed that whenever the zone is under natural ventilation mode, the exhaust fan operates to strengthen the air flow into the building.

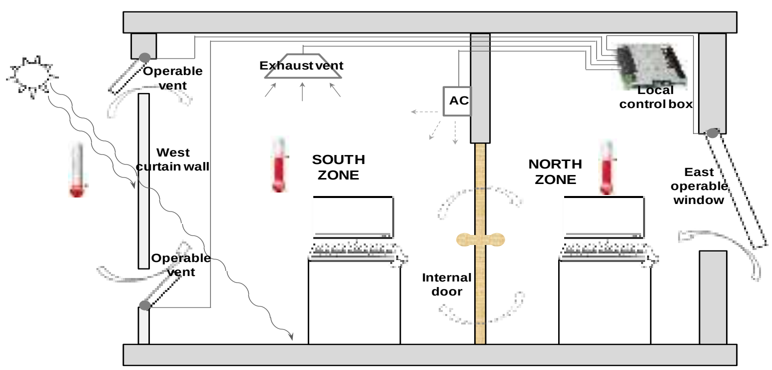

Figure 1: Test-building and the mixed-mode control system

2.2 State-space Model

The thermal dynamics of interior building zones are typically predicted by applying the heat balance method which explicitly models the heat transfer rate to the interior and exterior surfaces and to the zone air based on energy conservation. A thermal network of the building was built and heat balance was performed at each node to determine the node temperature and heat flow between connected nodes. Also the multi-zone airflow network method (Hensen, 1990) that represents building spaces by homogeneous nodes that are linked with other nodes through openings between spaces, is adopted to calculate the air exchange flow rates. Using the mass conservation for each zone and the "onion" coupling method, the air flow network and thermal model of the building and be used to calculate the convective heat transport due to air-exchange (Hu and Karava, 2014a; 2014b).

Thermal dynamics of the building with mixed-mode cooling can be formulated using the state-space representation as follows:

$$\dot{x} = Ax + Bu + f\left(x, u, \dot{m}\right) \qquad , \qquad y = Cx + Du \tag{1}$$

In which, A, B, C, D are coefficient matrices. x is the state vector that represents the temperature of each node. u is the input vector (e.g. outside temperature, solar heat gain, auxiliary heat supply or extraction rate) and y is the output vector (e.g. zone air temperature, wall surface temperature). This forward state-space model is nonlinear due to the term $f(x, u, \dot{m})$ that represents the heat transfer associated with the airflow and it can be linearized and discretized in time as follows (Hu and Karava, 2014b):

$$x_{k+1} = A_k x_k + B_k u_k \qquad , \qquad y_k = Cx_k + Du_k \tag{2}$$

Using this linear time varying state space representation (LTV-SS), a 53rd order model was establishedThe thermal network of the south office room, which is the focus of this study, is shown in Figure 2. Also details of the inputs, outputs and state variables are presented in Table 1. The input vector $u \in \mathbb{R}^{33}$ includes controlled inputs such as the heat extraction rate (provided by the HVAC system or natural ventilation) and uncontrolled inputs (disturbances), which are the exterior temperature (T_{ext}), solar gain on internal and external surfaces (S_{ij}), and the internal heat gain (Q_{IHG}). The matrix $C \in \mathbb{R}^{53\times53}$ is an identity matrix so that the output vector $y \in R^{53\times1}$ is identical to the state vector $x \in \mathbb{R}^{53\times1}$. D is a zero matrix. The matrices $A \in \mathbb{R}^{53\times53}$ (state matrix) and $B \in \mathbb{R}^{53\times33}$ (input matrix) can be found from the balance equations for each thermal node. Both matrices are time-variant as their elements associated with the airflow rate, convection and radiant heat transfer coefficients may vary with time.

Table 1: States, Inputs and Outputs used in the state-space model

States (x):	Inputs (u):	Outputs (y):
$x = [T_i , T_j, T_k]^T$ ▪ i: zone index ▪ j: surface index ▪ k: mass node index	$u = [T_{ext}, S_{ij}, Q_{IHG}, Q]^T$ ▪ T_{ext}: exterior air temperature; ▪ S_j: solar radiation on surfaces j; ▪ Q_{IHG}: internal heat gain; ▪ Q: heat extraction rate;	$y = [T_i , T_j, T_k]^T$ ▪ i: zone index ▪ j: surface index ▪ k: mass node index

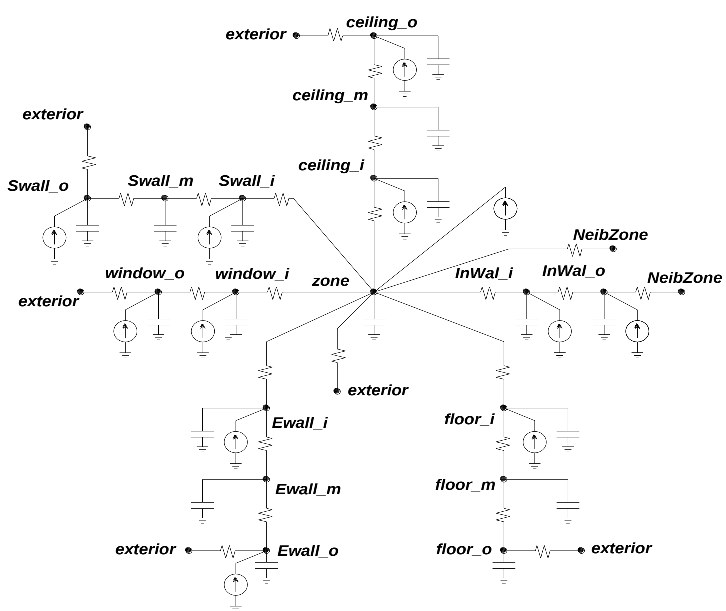

Figure 2: Thermal network of the south zone

2.3 Probabilistic Model of Blind Usage

In this study, a probabilistic model of occupants' behavior on window blind closing event is used to represent the disturbance due to interactions of occupants with the building. This is classified as pattern-prediction model and is derived from multiple logistic regression analysis and Generalized Estimating Equation (GEE) methods, based on a field study in office buildings (Inkarojrit, 2005). The field study data were collected from 25 participants who occupied private offices in Berkeley, California between September 2004 and February 2005.

Analyzing the blind occlusion data from surveys and field study, Inkarojrit (2005) found that during the closing event of blinds, most of them were lowered to the fully closed position and only a very small proportion of window blinds were closed half way. Also it was found that most, if not all, of the blinds were rarely adjusted for their slat angle and they were kept at the fully closed position (90 degree downward). It means that the chosen dependent variable for the window blind control logistic model was the window blind closing state (yes =1, no =0). To simplify the analysis process, if the occupants prefer to have their window blinds closed, based on the occlusion data, it is assumed that the window blinds and slat angle would be set to a fully closed position (Inkarojrit, 2005). Since a window blind with fully closed slat angle (90 degree downward) can be looked at as a window shade, we were able to provide an environment similar to Berkeley test-building by adding roller shades to the curtain wall of south zone in the test-building at Purdue. In this way, we were able to use the probabilistic model of blind usage.

According to use of different types of physical parameters as model variables, nine different multivariate regression models are derived for predicting the closing event of window blind (Inkarojrit, 2005). For the purpose of this study, along the nine models described by Inkarojrit, model M2 was used to calculate the probability of having a closed window blind at each time step of simulation. This model considers the vertical solar radiation on window surface and occupants' self-reported brightness sensitivity as variable parameters and predicts the closing event of blinds with 86.3% of accuracy.

The probability of window blind closing event could be estimated by applying the regression coefficient and constant to the following equation:

$$P(X) = \frac{e^{-(\alpha + \sum \beta_i X_i)}}{1 + e^{-(\alpha + \sum \beta_i X_i)}} \tag{3}$$

Where, $P(X)$ is the probability of window blind closing, X_i represents the variable parameters of the model and α, β are estimated regression coefficients.

For model M2 variables are vertical solar radiation at window (SOL) and self-reported brightness sensitivity (Lsen). The average self-reported brightness sensitivity during the surveys and field study was equal to 4.9 (measured on a 7-point scale, where 1 = least sensitive and 7 = most sensitive). This average value was used in application of model M2. Table 2 indicates the regression coefficients and constant for this model.

Table 2: Regression coefficients and constant for probabilistic model of window blind closing

	Standard Regression						GEE		
Variable	β, α	LR	R^2	% Correct	AIC	ROC Area	β, α	Wald	XT-Corr
SOL	3.09	40.9	0.62	86.3	50.8	0.92	3.22	13.82	0.14
Lsen	1.22						1.22		
Constant	-8.71						-8.94		

3. CONTROL FORMULATION

3.1 Heuristic Rules

In this study, the following heuristic rules were used for operation of natural ventilation in the building. That is, when following rules are satisfied, window is open otherwise; closed (Hu, 2014).

$T_{ext} \in [15\ °C, 25\ °C]$, $T_{dew} \leq 13.5\ °C$, $W_{spd} < 7.5$ m/s
A typical nighttime setback control strategy is applied with a set point temperature range from 13 °C to 30 °C (ASHRAE, 2010). To have a fair comparison between heuristic and SMPC, a blind control strategy was developed in heuristic model which doesn't let the blind be open when the incident beam solar radiation on the west surface at window is greater than 180 W/m^2.

3.2 Deterministic MPC

Model predictive control is a method of dynamic optimization in which multiple control decisions for a dynamic system are optimized sequentially. Due to optimization constraints, control decisions are optimized by minimizing an objective function which describes the cost of operating. MPC strategies for mixed-mode buildings aim to optimize the switching between free (natural) and mechanical cooling. In the presented study, the decision space is the operating schedule of the motorized windows used for free cooling and the objective is to minimize the energy use with comfort constraints. Optimal control sequences for the operation schedule of the motorized windows, which are integrated on the west-facing curtain-wall in the south zone, are formulated over a 24-hour planning horizon beginning from 20:00 to 19:00 on the following day. The MPC problem can be mathematically formulated as:

$$\text{Minimize: } J(\overrightarrow{IO}_t) = C = \sum_{i=1}^{24} \frac{|Load_i| \times 1hr}{COP} \quad (4)$$

Subject to: $\overrightarrow{IO}_t = \{0, 1\}$; $W_{spd} < 7.5$ m/s;
$T_{ope} \in [23\ °C, 27.6\ °C]$ during occupied hours;
$T_{setpoint} \in [21\ °C, 24\ °C]$ during occupied hours;

Where, $\overrightarrow{IO}_t$ is the vector of binary (open/close) decisions for the motorized windows and C is the energy cost (mechanical cooling) determined through the simulation and can be calculated according to summation of load demand during the next 24 hours. During the occupied hours (9:00 am – 5:00 pm), the set point temperature $T_{setpoint}$ is allowed to fluctuate between 21 °C and 24 °C (ASHRAE, 2010) while the same a nighttime setback control strategy as heuristic model is applied. The operative temperature T_{ope} during the occupied period is maintained between 23 °C and 27.6 °C, corresponding to 80% occupant satisfaction (Fanger, 2006), while this constraint is removed when the building is not occupied. Optimal decisions are also constrained by a maximum wind speed W_{spd} which is set to 7.5 m/s as suggested by Aggerholm (2002).

The performance of control strategies is evaluated in terms of the summation of the hourly mean energy consumption and the total operative temperature deviation from the desired range. The total operative temperature deviation is obtained from:

$$\Delta T_{ope} = \sum\nolimits_{occupied} \left|\Delta T_{ope}^{t}\right| \quad (5)$$

Where ΔT_{ope}^{t} is the operative temperature deviation from the desired range at time t during occupied period. The nature of this optimization problem doesn't allow traditional gradient methods to find the minima. Therefore, a progressive refinement (ProRe) optimization method is developed following the "multi-level optimization" topology (Goertzel, 1990) and branch and bound decision trimming strategy (Hu and Karava, 2014b; Chinneck, 2012). Since the purpose of this study is to compare SMPC and DMPC and not to investigate performance of optimization environment, the progressive refinement is not fully described here and the interested reader may refer to Hu and Karava (2014). The same blind control strategy was used in all cases considered here (heuristic, DMPC and SMPC) to ensure a meaningful comparison.

3.3 Stochastic MPC

In stochastic model-predictive control (SMPC) framework, the state at any future time is uncertain due to stochastic disturbances in the system, and the new formulation is to minimize the expected value of the cost function, given the set of possible disturbances.
In this study, the same optimization approach of DMPC with the same constraints has been used for SMPC as well to make the deterministic and stochastic controllers comparable. But the difference is that the cost function is not deterministic anymore and the expected value of cost function is being optimized. According to the fact that a constant value of COP has been assumed in this study, expected value of cost function would be expected summation of load demand over the next 24 hours with the same constraints as described for DMPC:

Minimize: $J(\overrightarrow{IO}_t) = E[C] = E[\sum_{i=1}^{24} \frac{|Load_i| \times 1hr}{COP}]$ (6)

At each time step of simulation the probability of window blind closing event is calculated. The stochastic model of occupant blind use requires a random number at each time step to generate unique evolutions of occupant behavior. Therefore, calculated probability is compared with a random number from the uniform distribution on the interval of [0,1]. If it is larger than the random number, some indicator function will be equal to 1 (closing action) and vice versa. When stochastic models are employed in simulations, they lead to uncertainty in simulation results, thus multiple simulations need to be conducted to arrive at a representative distribution of results. In order to find the expected value of cost function while accounting for stochastic effect of occupants' blind use, Monte Carlo (MC) simulation has been used in this study. During the optimization, a suite of simulations are conducted for each candidate vector of binary decisions to establish a representative result. Number of these simulations for each candidate, which is called number of MC simulations, should be sufficient so it can capture the stochastic effect of occupants' behavior in blind closing event. Choosing a set number of MC simulations a-priori is difficult because it is impossible to know in advance how many simulations will be required to capture the variability in stochastic model so if the chosen number of simulations is too low it might not be able to fully catch the stochastic effect. On the other hand, simulations are computationally expensive and for cases with a small range of variability chosen number may be too high. To deal with this problem, the methodology represented by Ata (2007) has been employed to determine when sufficient number of simulations has been performed. In this methodology two convergence criteria are defined: convergence band width B_W and convergence band length B_L. The band length is the minimum number of simulations and band width is expressed as percentage error of the average value of all simulations up to simulation n.

$$B_W = \%Error \times \overline{C}_n \quad , \quad \overline{C}_n = \frac{1}{n}\sum_{i=1}^{n} C_i \tag{7}$$

After computing the cost function of simulation n, we can compute the upper and lower bounds of the convergence band as $\overline{C}_n \pm \frac{B_W}{2}$. Then Equation (14) will ensure that for all last B_L simulations average cost is within the convergence band:

$$[\overline{C}_n - \frac{B_W}{2} \le \overline{C}_{n-k} \le \overline{C}_n + \frac{B_W}{2}] \forall k, k = 1,2,\ldots, B_L \tag{8}$$

Half of the band width indicates the level precision for MC estimate and can be set to ($\frac{10^{-d}}{2}$) where d is the desired number of significant digits after the decimal point. Also for a given band width and desired 100 (1-γ)% level of confidence, band length can be chosen from Equation (15):

$$0.9^{B_L}\{-\ln(0.1)B_L\}^{-1} \le \gamma \tag{9}$$

This stopping rule does not require sequential computation of the MC sample variance so it is computationally more efficient than the usual standard stopping rules. A maximum number of MC simulations can be chosen to constrain the runtime so that the MC simulation will stop once one of the following happens: either stopping criteria get satisfied or maximum number of simulations is reached. This number was chosen to be equal to 500 in this study.

4. SIMULATION AND RESULTS

In this section simulation results for SMPC, DMPC and heuristic control will be presented and their performance will be compared in terms of energy consumption and thermal comfort maintenance. For this purpose, the exceedance metric of "percentage outside the range" is defined as the percentage of occupied hours in a month when operative temperature is more than 10% out of the acceptable range; [23 °C, 27.6 °C] (Brager and Borgenson, 2011; ASHRAE, 2010). Despite the need, the current ASHRAE Standard 55 does not offer much guidance on comfort in mixed-mode buildings but similar European standard, EN 15251, states that since the criteria of thermal comfort are based on instantaneous values, values outside the recommended range should be acceptable for short periods during a day. Therefore, according to this standard, for 3-5% of the time the exceedance metric can be out of the desired range that is, a percentage outside the range less than 5% would be acceptable.

Since the main purpose is to exploit natural ventilation for cooling, simulation of the test-building was conducted for five warm months of May, June, July, August and September. Also since the goal of this study was to compare performance of different controllers and not to actually implement them in a real building, TMY3 data for Lafayette, IN was used for the purpose of this work. According to energy pricing, the desired number of significant digits after the decimal point for value of cost function, which is equal to summation of load demand for next 24 hours, was chosen to be two i.e. $B_W = 1\%$. Also confidence interval of 98% for MC simulation was selected which yields $B_L = 10$.

Figure 3 shows the calculated load demand and energy consumption for each month respectively. As it is clear from the figures, SMPC shows a considerable increase in load demand and energy consumption. Compared to DMPC, this increase was 17.9% in May, 21.3% in June, 10% in July, 17.0% in August and 20.9% in September. One can readily see that due to their assumption on neglecting the disturbances coming from occupants' behavior, deterministic and heuristic approaches can easily lead to considerable errors in predictions of load demand which in turn may affect the robustness of the control decisions.

Figure 4 demonstrates the Percentage outside the range for DMPC, SMPC and heuristic control. It can be seen that Percentage outside the range for heuristic control is always significantly higher than MPC. For instance, during the month of May, this value is almost 45 percent for heuristic control which is much higher than the corresponding values of DMPC and SMPC and also the accepted value of 5 percent. Although heuristic rules lead to least amount of energy usage among all three approaches (Figure 3) they result in significant number of thermal comfort violations. The Percentage outside the range has been shown using a larger scale for DMPC and SMPC in Figure 5. It can be seen that DMPC violates the maximum accepted value of Percentage outside the range during the three months of May, June and September while this only happens in May for SMPC. Besides it is clear from the chart that exceedance metric always has a lower value in performance of SMPC.

In SMPC model, due to different operation of shades, solar input to the system is different from DMPC and this will clearly result in different set of control signals for the window opening schedule. This has been shown in Figure 6 for some representative days of simulation for each month. In this figure dark cells represent open position of window.

Simulations were run on a regular office desktop computer. Running time for simulation of each month was almost 13 hours for following conditions: Two significant digits after the decimal point of average value of cost function, 98 percent confidence interval of MC simulation and 500 as maximum number of MC simulation. This roughly implies 25 minutes for each day which proves to be fast enough to be implemented in an online framework of MPC.

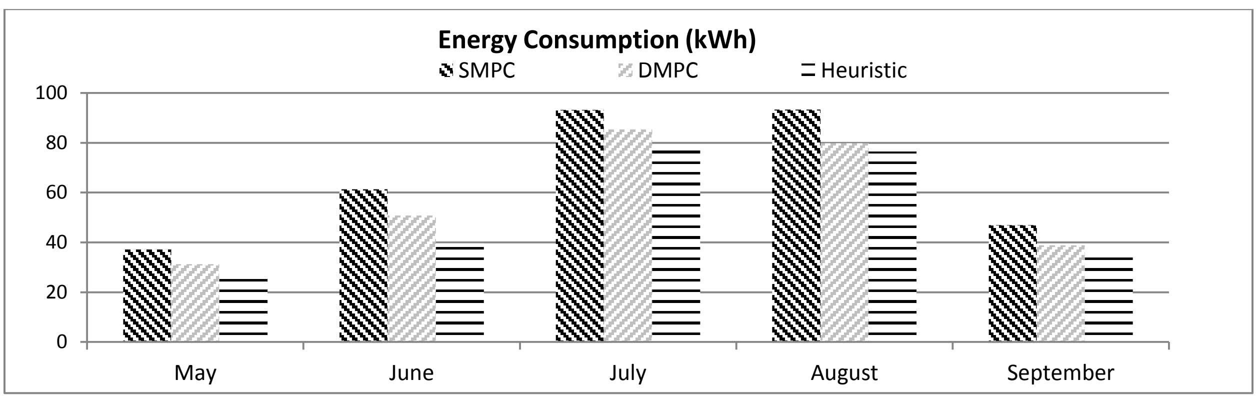

Figure 3: Calculated energy usage

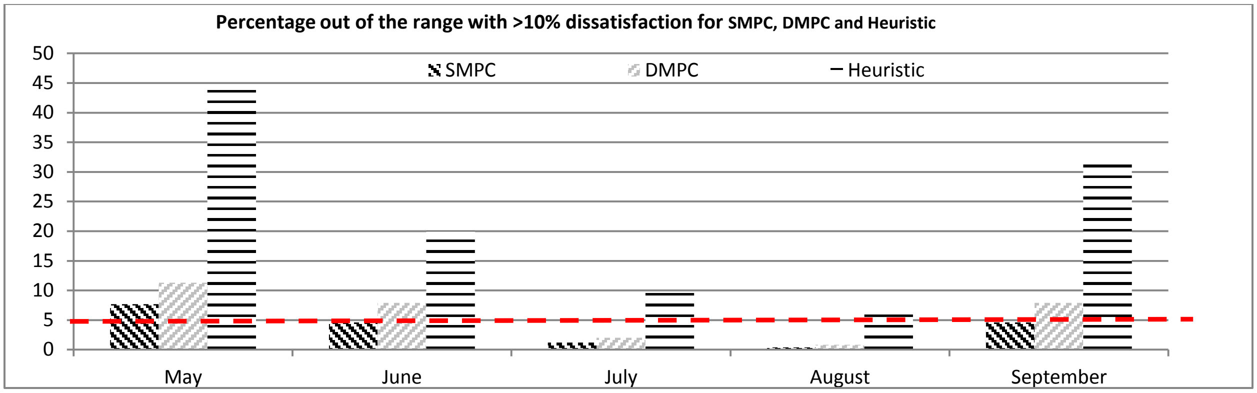

Figure 4: Exceedance metric for SMPC, DMPC and heuristic strategies

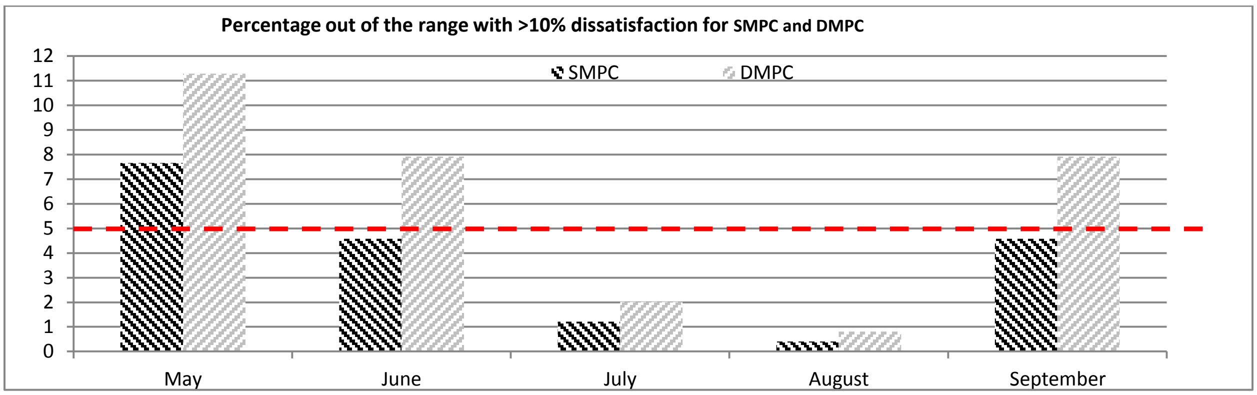

Figure 5: Exceedance metric for SMPC and DMPC (large scale)

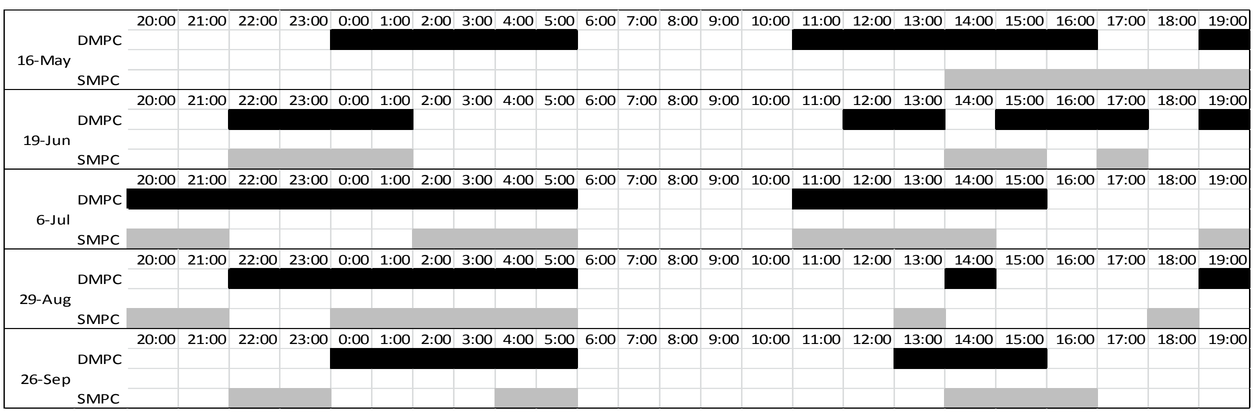

Figure 6: Window opening schedule

5. CONCLUSIONS

By implementing a pattern-prediction model of occupants' interaction with window blinds in a model predictive control framework and formulating the stochastic effects by means of Monte Carlo simulation, we were able to compare the performance bounds of stochastic and deterministic MPC for a building with mixed-mode cooling. It was found that SMPC leads to higher amount of energy consumption which provides a more realistic prediction since it considers the occupant-building interactions. Also it was found that SMPC results in lower thermal comfort violations than DMPC and significantly lower compared to heuristic control.

The probabilistic model of blind usage in this study accounts for interactions of occupants with only one of the building systems while actual disturbance of occupants comes from their interdependent interactions with each and every manually operable system of the building. For this reason it is important to develop pattern-prediction models that can take this interdependency into account. In order to have a more accurate model it is also important to combine disturbances of occupants with weather forecast and modeling errors. In this case, due to its expensive computational effort, Monte Carlo simulation might not be the best approach to account for stochastic effects and use of Markov chains in framework of Randomized MPC (RMPC) might be a promising alternative. Further research on these topics is currently performed by the authors.

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