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Occupancy behavior based model predictive control for building indoor climate—A critical review

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ABSTRACT

This paper reviews occupancy based model predictive control (MPC) for building indoor climate control. Occupancy behavior in buildings is stochastic and complex in nature. With better understanding of occupancy presence in rooms and spaces, advanced controls, such as MPC, can be designed to achieve a more energy efficient operation, compared to more traditional control methods, while comfort is maintained. This paper starts with an overview of traditional controls implemented in buildings, and importance of occupancy based controls. Various control-oriented building modeling methods including physics-based and data-driven models are reviewed. Later on, a comprehensive review of MPC in terms of control theory, objective functions, constrains, optimization methods, system characteristics and various types of MPC is presented conducted. In principle, MPC finds an optimal sequence of control commands to optimize an objective function, considering system model, disturbances, predictions and actuation constraints. Lastly, occupancy based controls including commonly used rule-based and latest model-based controls are reviewed. In addition, a few experimental studies are presented and discussed. The paper presents a holistic overview of occupancy-based MPC for building heating, ventilation, and air conditioning (HVAC) systems, and discusses current status and future challenges. The purpose of this paper is to provide a guideline forresearchers who would like to conduct similar studies to have a better understanding of established research methods.

Contents

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1. Introduction

1.1. Overview

Buildings are responsible for almost 40% of the whole energy use in the United States [1]. Reducing energy use in buildings is an important factor in dealing with CO_2 emission and global warming due to the fact that, buildings energy use stands for one-third of greenhouse gas emissions [2]. Additionally, buildings do not maintain a constant energy use during the day. 20% of the electricity production capacity is built only to meet the peak demand which is used only 5% of the time [3,4]. One of the biggest consumers of energy in buildings is air conditioning unit. About 40% of building energy is being used by HVAC system in commercial buildings. There are many research studies trying to reduce energy use in this section. There are many studies showing that up to 30% energy saving is achievable, switching from traditional methods of control to more efficient control methods. Most of the control methods used for HVAC are feedback controllers, such as proportional–integral–derivative (PID), and Bang–Bang controller. These controllers have been designed to maintain comfort rather than taking efficient control action. This makes the optimal control of this component crucial.

Model predictive controller (MPC) is a method to design sequences of control inputs to optimize an objective function considering defined and forced constraints. This controller uses the model of the system, system inputs, anddisturbances (e.g. outdoor weather, occupancy, solar gain, etc) to predict future states (e.g. indoor temperature) in order to make the most efficient control action [5,6]. This controller is suitable for controlling the HVAC system using weather and occupancy predictions and information available on energy peak price [3,4]. MPC can utilize building mass as a thermal energy storage or cold storage facilities for load shifting to off-peak hours [7–10]. MPC can be used to manage energy use from different available sources of energy in micro-grids and buildings [11,12]. MPC can be used to manage free sources of energy such as solar radiation through controlling window blinds [13]. MPC can result in about 27% energy saving for the air handler unit in a multi-zone building [14]. MPC can be used in HVAC energy management for interconnected water and air side to find an optimum controller for different situations [15]. MPC can use occupancy predictions or schedule to minimize energy use while maintaining comfort. Most of research papers show that using MPC to control HVAC system or room temperature can save ten to fifty present energy depending on controller configuration, and disturbances predictions [14,16–23]. There is a simulation report from Pacific Northwest National Laboratory (PNNL) on occupancy based Variable Air Volume (VAV) box control in 4.4 billion ft^2 commercial buildings (6% of total commercial floor space) in different climate zones showing an energy saving opportunity up to 23% by controlling VAV air flow based on room occupancy sensors [24].

1.2. Traditional control methods for HVAC system

The nonlinear and complex dynamic characteristic of HVAC system has made control a challenge. This challenge becomes even more difficult considering uncertain and time-varying environment and disturbances. In addition, building operators are interested in having an optimal controller to minimize cost in their system, which will add some other important factors to the problem, such as: optimal control methods, system modeling, etc.

Building automation system (BAS) provides a centralized management system to control heating, ventilating, air conditioning, lighting, safety and security to achieve occupant comfort and efficient building operation [25]. Most of control methods used in BAS can be divided into two main categories: supervisory and local controllers. Supervisory (High-level) controller tries to define set points for local controllers to achieve cost-efficient thermal comfort without violating system constraints [26]. Local (low-level) controllers, control each component of the system and bring functionality to the system. This category can be divided into two subcategories: sequencing and process control. Sequencing control turns each component on and off, while process-controller, brings each component states to desired values [27]. Building climate control can be as simple as a thermostat in a small residential building or as complex as a network of sensors and VAV boxes in a commercial building.

Different control methods can be used for building climate control. In [28] Optimal, MPC, PID, Robust, Nonlinear and adaptive controllers are reviewed as hard controllers. Optimal and model predictive control methods are known for their attractive capability of energy saving. Between these two, MPC can deal with model uncertainties and disturbances. Also, robust controllers are known for their capability in dealing with model uncertainties and disturbances [29]. There are a few papers studying nonlinear and adaptive controllers which can deal with system nonlinearity and adapt to small changes in the system respectively. Among all these controllers, PID, step and Bang–Bang controllers are more popular, due to their simplicity and ease of implementation. However, the on-off controller shows a big swing from the set point, and PID controller parameters tuning is a challenge in time-varying environments [30].

Model predictive controller is not a new control method. However, due to high computational cost of this method, it has not been attractive to researchers for building control in the past. To the best of the author's knowledge, there are many early studies trying to design optimal controller for HVAC system [31–33]. The idea of using optimization techniques to reduce energy use can be tracked back to 1970's [34]. MacArthur et al. [35,36] used receding horizon and model predictive control to minimize energy use in buildings in 1993. In 1999 Wang used TRNSYS to simulate building and HVAC system to test his optimal supervisory controller[37]. To the best of the author's knowledge it has been less than ten years that, this controller has received the attention of researchers in buildings' climate control.

1.3. Importance of occupancy-based controls

Human spend about 87% of their time in buildings [38]. Building energy consumption is a systematic procedure comprehensively influenced by not only engineering technologies, but also cultural concept, occupant behavior and social equity, etc. Occupancy behavior commonly refers to occupancy presence and counts in a space or a building, and human building interactions, such as opening/closing windows, blinds, and turning on/off lighting, as well as occupant preferences, such as thermal and lighting comfort. Occupant behavior becomes one of the leading influencers of energy consumption in buildings. There are many energy-saving opportunities available by having information on occupancy behavior. There is a simulation report from Pacific Northwest National Laboratory (PNNL) on occupancy based Variable Air Volume (VAV) box control in 4.4 billion ft^2 commercial buildings (6% of total commercial floor space) in different climate zones showing an energy saving opportunity up to 23% by controlling VAV air flow based on room occupancy sensors [24]. Information on occupancy presence can be used in controlling different devices such as: (a) lighting control based on occupancy presence; (b) zone temperature control based on occupancy presence; (c) ASHRAE ventilation rate requires cfm per person; (d) electric vehicle charging scheduling based on occupancy schedule; (e) appliances control based on occupancy preference, etc. In this paper, we will review those occupancy-based controls in details.

1.4. Summary of previous reviews

Many researchers have published review papers on buildings' climate control and related areas [26,39–44]. In [26] different methods of supervisory control and optimization methods have been reviewed. Different methods of modeling HVAC system for control and simulation purposes has been summarized in [45]. Modeling and simulation of occupancy behavior in offices has been discussed in [46]. Occupancy measurement and modeling has been reviewed in institutional buildings in [47]. In [48], lighting control system with occupancy detection methods has been discussed. In [39] control methods of HVAC system with focus on MPC has been reviewed. However, this paper will focus on occupancy-based MPC for building climate controls from theoretical framework to experimental studies.

The rest of this paper has been organized according to building and HVAC modeling, control theory of MPC, building climate control, simulation and experimental studies. First of all, different modeling techniques used for thermal behavior of buildings in MPC design are presented. Secondly, different occupancy measurement and behavior modeling methods are summarized. Thirdly, theory of model predictive control and performance of this controller are included. In addition, different types of MPC configuration used in occupancy-based controls are reviewed including commonly used optimization methods, different objective functions, constraints, other MPCs, and uncertainties effect. Fourthly, case studies of occupancy-based controls including both rule-based and MPC-based are reviewed in section four. In addition, experimental studies with real-time implementation of occupancy-based MPC are reviewed. Finally, this paper is concluded with a summary of what has been achieved in all previous researches and what are open issues for future studies.

2. Modeling

Model predictive control requires system model to perform prediction on states of the system. The very first model needed by MPC is the building model. In order to obtain required inputs to

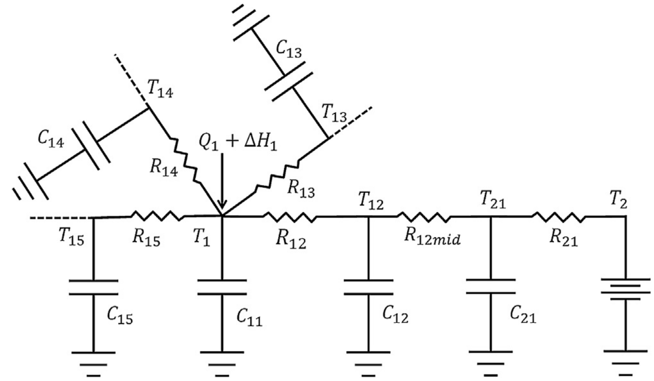

Fig. 1. RC Network model.

the building model, other models and predictions are required, including: HVAC system model, occupancy prediction, internal load prediction, weather prediction, etc. In the next two sections different methods of building thermal modeling and occupancy behavior modeling for MPC design are reviewed.

2.1. Control oriented building modeling

Building/HVAC thermal models can be divided into three categories: physics-based, data driven, and grey box. Physics-based models use physical model of each component to describe system dynamic. Therefore, parameters of such models have a physical meaning. Physics-based models have more capabilities in generalization but less accuracy in comparison to data-driven models. Data driven (black box) models have more accuracy within the scope of training data but less generalization capabilities. Grey-box models stands in between using both features from physics-based and data-driven models to achieve better results [49].

2.1.1. Thermal Network Model

Thermal Network Model is the most used physic-based model in building indoor climate control. Within this model, walls are modeled as resistance between each thermal zone with thermal storage capacities. Zone mass is modeled as capacitors, representing thermal storage. In the commonly called 3R2C model, walls are modeled with two capacitors and three resistances. In the following notation C_{11} is room thermal capacity T_1 is room temperature, $R_{12}, R_{13}, R_{14}, R_{15}$ are thermal resistances for four internal walls around zone 1. R_{12mid} is resistance for wall between zone 1 and 2. $T_{12}, T_{13}, T_{14}, T_{15}$ are temperature of internal walls. Q_1 is internal heat for zone number 1. ΔH_1 is input enthalpy to the zone. Eq. (1) is temperature dynamic for zone 1. Eqs. (2) and (3) are thermal dynamic for the wall between zone 1 and 2 (Fig. 1).

$$C_{11}\dot{T}_1 = -\left(\frac{1}{R_{12}} + \frac{1}{R_{13}} + \frac{1}{R_{14}} + \frac{1}{R_{15}}\right) \times T_1 + \frac{T_{12}}{R_{12}} + \frac{T_{13}}{R_{13}} + \frac{T_{14}}{R_{14}} + \frac{T_{15}}{R_{15}} + Q_1 + \Delta H_1 \tag{1}$$

$$C_{12}\dot{T}_{12} = -\left(\frac{1}{R_{12}} + \frac{1}{R_{12mid}}\right) \times T_{12} + \frac{T_{21}}{R_{12mid}} + \frac{T_1}{R_{12}} \tag{2}$$

$$C_{21}\dot{T}_{21} = -\left(\frac{1}{R_{21}} + \frac{1}{R_{12mid}}\right) \times T_{21} + \frac{T_{12}}{R_{12mid}} + \frac{T_2}{R_{21}} \tag{3}$$

ΔH_1 is input enthalpy to the zone calculate from supply air and exhaust air enthalpy difference Eq. (4). m_1^{SA} is supply air mass. m_1^{EA} is exhaust air mass. h_1^{SA} and h_1^{EA} are supply and exhaust air enthalpy to the zone 1. C_a is air specific heat capacity. C_w is water specific heat capacity. h_e is evaporation heat of water.

$$\Delta H_1 = m_1^{SA} h_1^{SA} - m_1^{EA} h_1^{EA} \tag{4}$$

$$h_1^{SA} = C_a T_1^{SA} + W_1^{SA} \left(h_e + C_w T_1^{SA} \right)$$

$$h_1^{EA} = C_a T_1 + W_1 \left(h_e + C_w T_1 \right)$$

Humidity dynamic can be represented by gas laws. n_1^p is number of people in zone 1. w_p is water vapor produced by a person. W_1^{SA} is supply air humidity.

$$\dot{W}_1 = \frac{RT_1}{V_1 P} \left(n_1^p w_p + m_1^{SA} \frac{W_1^{SA} - W_1}{1 + W_1^{SA}} \right) \tag{5}$$

There are several studies showing that second order 3R2C model is more accurate than the first order RC model in capturing thermal behavior of a building. Also, there is not significant improvement using higher order models [50]. There are several studies on identifying RC models parameter. In [51] extended Kalman filter has been used for a dual-estimation problem for estimating parameters and states of RC models of a six story building. Then the models have been compared in capabilities of capturing system behavior. In [52] a detailed model is presented using frequency response analysis. Also, three resistance-capacitance models are presented and parameters are identified using an optimization routine. In [6,53] nonlinearity of the building thermal model has been identified, and inverse function of the nonlinearity has been used to achieve a total linear model in order to formulate linear programming to solve the optimization problem for MPC.

2.1.2. Modeling software

There are some studies using thermal modeling software, linked with an optimization software to run MPC. There are numbers of simulation software for building thermal modeling. ASHARE is supporting TRNSYS, HVACSIM+, and EnergyPlus, While U.S. Department of Energy is maintaining BLAST, BSim, ESP-r, and DOE-2. There are some applications for optimization purposes using other programs as simulation engine [54]. GenOpt can use EnergyPlus, TRNSYS, IDA-ICE and DOE-2 simulation software to optimize the objective function [55]. However using a detailed software for building model in MPC won't necessarily end up in a better results [56].

2.1.3. Data-driven and gray-box models

There are many studies using system identification methods [57], NN, SVM[58], Fuzzy logic [59], ANFIS and FAN to model HVAC. Optimization methods, such as genetic algorithm can be used to identify RC network parameters [60–62]. In [20] one week on data were used to estimate RC network parameters solving optimization problem to minimize error with interior-reflective Newton method. In [19] nonlinear regression were used to identify RC network parameters. To ensure stability of MPC using online identified models, some studies use constrained parameter estimations. In [21] constrained parameters were identified every night using new measured data to reduce model error in MPC.

2.2. Occupant measurement and modeling for control purpose

To measure occupancy, passive infrared sensor (PIR) can be used, which is one of the most used sensors. However, such sensors cannot measure number of people. Combination of PIR sensor data with CO_2 or camera can be used to achieve a more accurate measurement for number of occupants [63,64]. There are some attempts to use human as a sensor to control the HVAC system, which can result in a more accurate comfort control, if the human feedback be available all the time [65,66].

Along with measurements, a good predication of occupancy profile is required to do pre-heating (pre-cooling). Prediction of occupancy is also important for pre-ventilation of zones when the room is first being occupied and the air conditioner unit can run with its best performance [67,68]. Markov chain models can be used to predict occupancy behavior, based on previous occupancy measurements [69,70]. In most cases, the number of occupants in the room cannot be observed directly. In this case the occupancy presence or quantity is the hidden state, and the sensor data or system output is the observable state for a hidden Markov model [71]. There are some other studies comparing neural network, support vector machine and hidden Markov model in detecting the number of occupants in a building [72,73]. Different methods of modeling occupancy as a probabilistic disturbance can affect controller performance, which makes the choice of the method an important factor [74,75].

3. Model predictive control for building indoor climate

MPC can be used when sequence of decisions affects energy efficiency of a building. The efficiency of control actions depends on controller configuration. MPC can be configured with various types of objective functions and constraints. In addition, the amount of disturbance predictions and accuracy can affect MPC performance. Furthermore, MPC can be formulated in centralized, decentralized, distinct and stochastic structures [39]. In the following section different building models, objective functions, constraints, optimization methods, and structures, are summarized.

3.1. Theory of MPC

MPC is a control method, using system model to predict future states of the system to make an optimal control action. Optimal control actions to satisfy an objective function are calculated by solving an optimization problem in every step of controlling a system. The optimization problem can be formulated in general form of:

$$\begin{aligned} & \min f\left(x_{t\to t+N|t}, u_{t\to t+N|t}\right) \\ \textit{subj to}:\ & x_{t+k+1|t} = \mathrm{g}\left(x_{t+k|t}, u_{t+k|t}\right), \mathrm{k} = 0, 1, \ldots, \mathrm{N}-1 \\ & x_{t+k|t} \in \mathrm{X} u_{t+k|t} \in \mathrm{U} \end{aligned} \tag{6}$$

Where $x_{t+k|t}$ denotes $(t+k)th$ predicted state of the system at step t. $u_{t+k|t}$ represents input vector to the system, calculate at step t. System behavior is modeled based on initial states from measurements and predicted disturbances to the system. Input to the system in step t, is selected by solving the optimization problem for N steps. This optimization problem is solved for a specific time length (prediction horizon). Then the first or a portion of the inputs is introduced to the system as its optimal input. This process is repeated all over again to calculate the control signal in every step [76]. Fig. 2 illustrates how predicted output is used to produce control signals.

3.2. Objective functions

When designing optimal building climate control, whole building energy consumption, overall system efficiency, operation cost, building related greenhouse gas emissions, occupant thermal comfort, indoor temperature set-point, and electricity cost are commonly used as objective functions [77]. For example: In [78], thermal energy input and zone temperature weighted by the probability of the room being occupied has been used as the objective

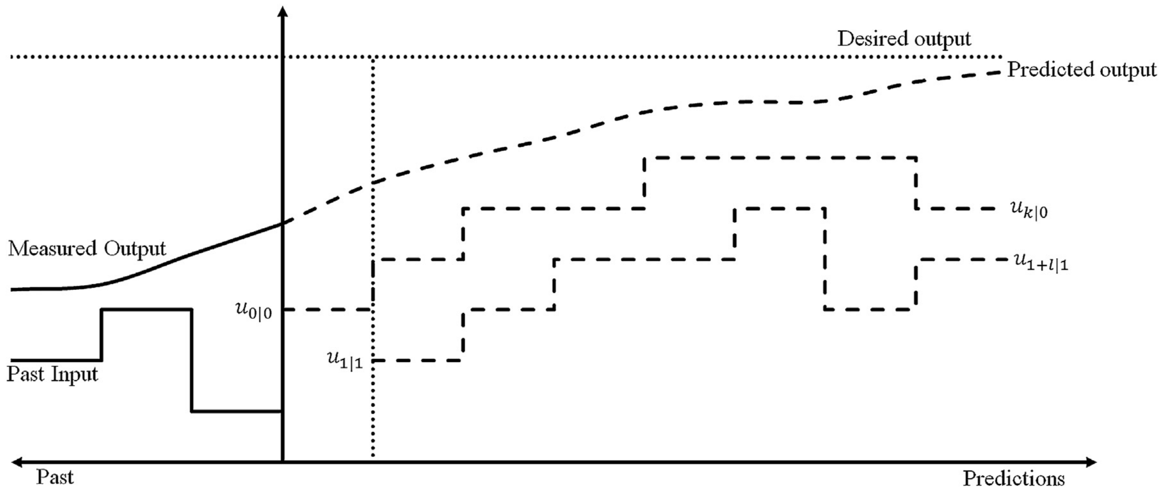

Fig. 2. Receding horizon control actions.

function. In [21] CO_2 emission along with overall cost has been used as objective function. In [56] Predicted Mean Vote (PMV) index and energy cost has been used as objective function. In [62] two objective functions have been put in contrast: PMV along control signal and PMV along room temperature changes. PMV along control signal resulted in a better performance. On the other hand, relative humidity and zone temperature error from set-point, along with total energy consumption can be used as an objective to maintain zone comfort in psychrometric chart and minimize energy consumption [79]. Following table summarizes objective functions used in various building climate control papers (Table 1).

3.3. Constraints

One of the most important constraints for the building climate control optimization problem is human thermal comfort. Defining thermal comfort in building is cumbersome due to human complex dynamic. There are two main methods to introduce this constraint to the problem: predicted mean vote (PMV) [94] and Thermal bounds. PMV was first introduced by Fanger [94] in 1970. There are a few other mathematical models to determine occupancy thermal sensation and comfort [95,96]. Predicted Percentage of Dissatisfied (PPD) can be defined as the percentage of people who are not satisfied with a specific PMV value. PMV and PPD can be used as a constraint to MPC problem [79,85,97]. In [81] a data-driven Wiener-logistic comfort model has been used as a constraint to a stochastic and deterministic MPC problem to optimize energy use and occupancy comfort. Using MPC with PMV constraint or objective function can be computationally expensive. Therefore, PMV formula linearization can decrease optimization complexity [56].

Actuation and physical limits are some of the main constraints for optimization problems. Almost all of these upper and lower bounds are linear. Another important constraint is the dynamic model which predicts future states. This constraint is nonlinear in most building control design cases. Another interesting part is stochastic constraints, which introduce the probability of an event happening to the problem. This kind of constraint makes the problem nondeterministic, so they are commonly replaced with a deterministic constraint.

There are a few other optional constrains which can affect MPC performance and goals. Ref [21] have used equipment efficiency as a constraint to increase overall efficiency. Ref [54] has considered operational duration as some countries have some restrictions on HVAC operating hours.

3.4. Optimization methods

The most popular optimization methods in HVAC supervisory control design are: sequential quadratic programming (SQP), direct search, Lagrange method, univariate search, conjugate gradient method, branch and bound (BB) and evolutionary methods [26]. However, in MPC building climate control design, gradient based optimization algorithms will have difficulty solving the problem due to complexity of optimization problem for buildings. Meta-heuristic evolutionary algorithms, such as Genetic algorithm [54,90] and particle swarm optimization [98] can be used to solve MPC problem. Linear programming [13], mixed integer programming, dynamic programming, and quadratic programming are the most used method in building thermal control. Table 2 summarizes optimization methods and software used by different studies in building thermal model predictive control with occupancy. Fig. 3 shows different configuration of MPC used in building thermal control.

3.5. Decentralized MPC

The size of the model of a building can grow fast with number of rooms, which leads to expensive computational effort for MPC. Decentralized MPC provide a solution by breaking down the building dynamic into multiple decupled smaller equations to be solved separately. Sequential quadratic program (SQP) and dual decomposition has been used to design a distributed MPC with occupancy and weather predictions in [99]. In [100] distributed MPC has been presented to control energy distribution between agents (rooms) of the system with renewable energy sources in the loop. The results show that decentralized model predictive control (DMPC) can provide near optimal solution with less computational effort. In [88] a network of MPC controllers has been simulated as a distributed controller. Each MPC has access to neighborhood zone average temperature. In this study, dynamic programming approach has been used to produce an analytical solution to distributed problems. In [101] distributed MPC has been presented using Benders' decomposition approach for multi-source multi-zone building to minimize heating utility bills. The control scheme has been put in contrast with P-I controller. In [92] subgradient dual decomposition method has been used to decentralize stochastic MPC with predefined probabilities. The linear problem with energy cost, and slack variables cost function has been solved using linear programming method. This study show that distributed MPC result in almost fourth time computationally faster solution for a ten-zone building.

Table 1
MPC objective function for building climate control and Savings compared to traditional controllers.

Study	Objective terms										Mathematical Form				Savings
	Energy	Utility Cost	Occupancy presence	Comfort	CO_2 emission	Control signal	Performance	Temperature error	System states	Slack Variables	Linear	2nd norm	Quadratic	Non Linear	
[78]	X													X	19%
[21]		X			X								X		19% and 32%
[56]		X		PMV									X		10–15%
[62]				PMV				X				X			–
[62]				PMV		X						X			–
[79]	X			X									X		
[80]	X													X	10–48%
[20]	X													X	17.8%–30.1%
[16]	X													X	40%
[81]	X										X	X			
[19]	X							X					X		30%–70%
[82]		X												X	20%–70%
[22]	X		X										X		44%
[83]	X										X				31%–33%
[17]	X													X	12–37%
[84]	X										X				50%–70%
[85]	X			PPD				X					X		
[86]													X		4–58%
[87]	X													X	12%
[88]		X		X									X		
[63]						X			X				X		
[89]	X													X	5–44%
[90]	X			PMV										X	12%
[12]		X		PPD										X	12–22%
[54]		X		PPD										X	56%
[91]		X				X		X					X		
[92]		X								X	X				
[93]		X									X				

Table 2
Optimization methods and software used for solving occupancy related MPC problem in building thermal control.

Study	Building HVAC Model	Building Type	MPC time steps	MPC Prediction horizon	Optimization Method	Software
[80]	RC, Parameters chosen	commercial building, room-level climate control		30 and 120 min	BFGS	IPOPT Matlab
[16]	RC Physics-based	commercial building one room				IPOPT Matlab
[20]	3R2C Estimated parameters	Solar House test-bed office	15 min	Heating 24 h Cooling 3 h	dynamic programming	Matlab Simulink
[19]	RC	student computer laboratory	15 min	5 h		Matlab SNOPT solver
[82]		commercial building		3 h	interior-point nonlinear programming solver	IPOPT
[22]	Linear	Single-zone building	1 h	24 h	dynamic programming	
[87]	RC state-space		15 min	1 h		CVX
[21]	Physics-based, Parameters identified every night	Commercial two office buildings 3-floor 3322 and 1808 square meter	5 min		Quadratic programming	
[88]	state-space model	Two-zone	30 min	24 h	Dynamic programming	
[63]	Linear	Office site		90 min	least-square	MATLAB
[83]	RC and CO_2 model	laboratory room 80m2	10 min	9 h	MPT, parametric programming	MATLAB
[17]	RC	One zone				MATLAB
[84]	RC	Four 60 m2 rooms			MILP, LNS	Gurobi 5.6
[86]	RC	Two buildings		24 h		MATLAB TRNSYS SCADA
[89]	RC Physics	Single room office				MATLAB Simulink
[90]	Physics based	Multi-zone 8 zone commercial	1 min	5 min	GA	TRNSYS
[12]		Three building, 10 zones			Dynamic programming	EnergyPlus
[56]	LTI	TRNSYS	30 min	8–32 steps	Quadratic programming	TRNSYS Matlab
[79]	Linear	single-zone building		10 steps	quadratic programming	
[54]	EnergyPlus	Multi-zone		24 h	GA	MATLAB EnergyPlus
[91]	RC	Single Room	1 min	1 h	quadratic programming	

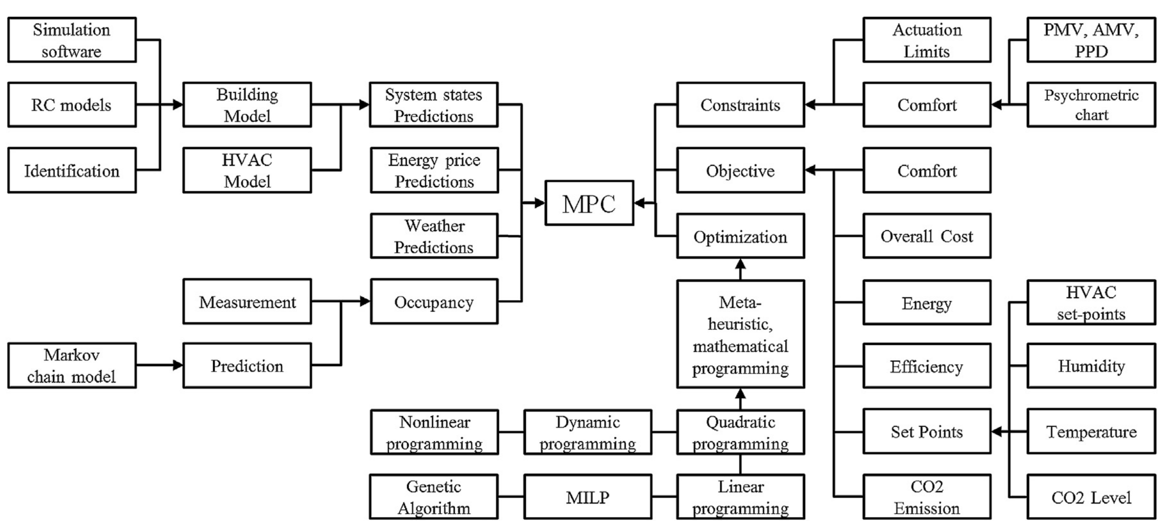

Fig. 3. MPC configuration.

3.6. Stochastic MPC

MPC requires future information on most of the system and environment states, including: room and outside temperature, energy price and occupancy. Most of these predicted data have stochastic behavior, which makes the use of stochastic model predictive control (SMPC) essential [92]. In [91] Markov chain model has been used for prediction for SMPC which resulted in 38.3% energy saving compared to PI controller. But it increased complexity of the system. In [93] an experimental evaluation was done on a student laboratory to test SMPC with occupancy and weather predictions. This study estimate 5–35% energy saving is achievable

Table 3
System characteristics and their effect on MPC performance.

System characteristic	Effect
Longer unoccupied periods	MPC with occupancy predictions can use a big set-back to reduce energy use in unoccupied periods and also pre heat before the occupancy.
Bigger thermal mass	MPC with energy price prediction can use the thermal mass to benefit off-peak hours.
Higher changes of weather in a day	MPC combined with weather forecasting can advantage outside temperature changes.
Broader range in reference temperatures	Optimization problem in MPC can give a better results with more relaxed constraints
Higher solar gains and free sources of energy	MPC can utilize free sources of energy in an optimum manner

using this controller. In [102] the author has used weather forecasting as an stochastic variable in solving SMPC. The result of this research shows that stochastic MPC can have a better performance than deterministic MPC. Results in [103] show that SMPC can result in 2% more energy saving than MPC using weather prediction.

3.7. System characteristic effect on MPC performance

MPC performance depends on system characteristics and problem structure. Solving a nonlinear optimization problem can be cumbersome if the system has many states and is too complex. Finding a global optimum solution can be computationally expensive for big and nonlinear problems. On the other hand, using a simplified model can result in less accurate control actions. Beside the structure of model predictive control, system characteristics can also affect the performance of this controller. MPC can reach a better performance in buildings with: longer unoccupied periods, bigger thermal mass, more available sources of energies, higher solar rates, higher ventilation, and slow HVAC system [104]. The effect of system characteristics on MPC performance are explained in the following table (Table 3).

3.8. Uncertainties effect

MPC needs prediction of states and inputs on the system to produce control actions. All these predictions and models introduce uncertainties to the system. In [17] the effect of different sources of uncertainties on MPC performance has been studied in simulation. This study shows that errors in occupancy measurement and model uncertainties have the strongest effect on MPC performance. This study shows that the plant model mismatches can change energy consumption up to 35% and occupancy fluctuations can change energy consumption up to 25%. However, errors in measuring outside temperature and solar load do not have a strong effect on MPC performance. It has been shown that even with these errors, MPC controller can deliver 12–37% energy saving compared to conventional controller. The building modeling can affect MPC performance, as energy consumption in the building model can deviate from the real energy consumption [105]. It can be shown that mismatching internal heat modeling can affect the performance of MPC for thermal energy storage [106].

4. Occupancy-based building climate control

4.1. Rule-based control

There are many studies trying to control building climate using occupancy measurements [107–111]. There are some studies using occupancy measurement to automate lighting in building [107,112–115]. Any occupancy based control need a reliable occupancy measurement. WI-FI enabled cellphones can be used to measure number of people in each zone. The use of cellphone WIFI signal will eliminate the cost of implementing a network of sensors in the building. However, it stands on the assumption that every person has a Wi-Fi enabled cellphone with him. The experimental results in [23] show 86% accuracy in measuring occupancy in a campus size building, which resulted in 17.8 percent energy saving. There are a few studies trying to use GPS enabled phones to predict occupancy in buildings. Ref. [116] introduced an application to remotely control a thermostat, which resulted in 6.3% energy saving. This study used GPS data to predict occupancy in buildings with 92.1% accuracy. The combination of information from GPS and WI-FI on mobile phone with a mobile application for building climate control can be a powerful tool in building energy management system. In [65] a simulation has been performed to control offices temperature based on occupancy feedback from mobile app and PIR sensors, resulting in 60% energy saving compared to fixed temperature control. In [117] PIR sensors has been used for two weeks in ten offices to measure occupancy presence, which can result in 10% to 15% energy saving based on simulations. Ref. [118] introduces an algorithm for pre ventilating each room based on occupancy measurement of neighboring rooms, which resulted in 6.1-19.7% energy saving compared to full-proactive control. In this method each unoccupied room is pre-conditioned if its neighbor room is occupied. This method can be utilized in an adaptive scheme based on frequency of changes in occupant presence in each room. In [119] particle filter prediction method has been used with a logical actuation algorithm to control ventilation. This study shows that 30% energy saving is possible using occupancy measurement. This study points out implementation difficulties in such a system, as buildings get larger. In [69] PIR sensors data has been used to train a Markov chain model to predict occupancy, which resulted in 42% energy saving using a rule-based controller compared to baseline controller. In [120] a Markov model has been trained using questioner resulted in 35.9% energy saving in simulation. In [121] a network of cameras has been used as occupancy sensors to control HVAC based on measurement and predictions resulting in 20% energy saving in simulation. Most of the time, overtime works in companies is not considered in designing a schedule for occupants in work places. There are some studies trying to model the number of occupants in the building after regular working hours in commercial buildings [122]. In [123] occupancy arrival and departure in commercial buildings was modeled with data from PIR sensors, which resulted in 10–15% energy saving in EnergyPlus simulation.

4.2. Model predictive control

In a simple rule-based scenario, occupancy measurement is used to save energy in unoccupied periods. However, thermal comfort cannot be guaranteed upon occupancy arrival. Therefore, MPC is needed while having occupancy prediction information. In [90] occupancy measurement is used to minimize energy use while maintaining air quality and occupant comfort in a multi-zone building. In this study, occupancy comfort, energy consumption, and indoor air quality has been used as cost function. This simulation shows up to 12% energy saving is achievable considering number of occupants. It can be shown that use of model predictive control just to minimize temperature error from the comfort zone can result in a higher air quality compared to conventional controller [124].

In [125] four air conditioning control methods have been put in contrast for complexity and performance: Baseline controller with and without occupancy measurements, optimal control with occupancy measurement and MPC with occupancy prediction. Among MPC methods using prediction or measurement; MPC with prediction results in more energy saving and less comfort violation compare to other methods. There is another research showing that, simplified controllers can perform as well as complex model based controllers on occupied periods [89].

When occupancy measurement is being used, the room condition can differ from comfort point at the very beginning of the room being occupied. This problem can be solved by using prediction methods to calculate the probability of the room being occupied. In such method, a room will be conditioned if the cost of occupant being uncomfortable is greater than the cost of conditioning the room. In [78] Markov chain model has been used to model the probability of the room being occupied. In this study, the MPC problem is formulated with energy input to the room and weighted set point error. The weight of the set-point error is the mean value of probability of the room being occupied [22]. In [18] Blended Markov chain has been used to predict load and occupancy for MPC resulting in 15.5% energy saving in summer and 9% energy saving in winter, in contrast to rule based controller with occupancy schedule. In [19] a Learn-based model predictive controller is introduced for a single-stage heat pump air conditioner. In this method the heat generated in the room is estimated based on the room model, AC Input and room temperature, to measure people activities in the room. The experimental evaluation of this method shows more than 30% energy saving over Two-Position Controller. Table 4 summarizes most of the research in building climate control using MPC and occupancy.

Some studies try to schedule meetings in an energy optimum fashion, where a lot of meetings are held every day [84,135]. Thermal energy efficiency of each room can change during the day. In addition, a preheating is needed before each meeting, and eliminating some rooms to be occupied in a day can save energy. In [84] the problem of meeting scheduling has been studied considering building model. And then the nonlinear optimization problem has been relaxed to a mixed-integer-linear- programming (MILP) problem.

4.3. Experimental studies

There are a few notable experimental studies on occupancy-based MPC. This section summarizes some occupancy based HVAC experimental studies comparing different control methods. A seven day long experiment was conducted a twelve story building, testing the rule-based controller using occupancy measurements [136]. A network of wireless sensors (PIR, CO_2, temperature and humidity) were used for occupancy measurements. A baseline with setback rules was used to control zones temperature. This research resulted in an average of 37% energy saving. Another seven-day experiment was conducted in the same building to test baseline controller with occupancy measurement in under-actuated rooms. This research resulted in significant energy saving using occupancy measurements in under actuated zones [126,128]. Another experiment was conducted in one room within the same building to compare baseline, rule-based controller with occupancy measurement, and model predictive controller with occupancy measurement. Results of this experiment shows both rule based and MPC controllers which use occupancy measurements save significant amount of energy [16].

An experiment was conducted in one floor of a four story building during fall and spring. A network of wireless sensors was used to measure occupancy presence. Electricity savings of 9.5% to 15% was measured in the EMS using occupancy data [137]. A twenty-day experiment was conducted in a seven-room, 1400 square foot house using occupancy measurement to test feasibility of room-level zoning [138]. In [139] a network of wireless sensors was used to measure occupancy presence and use occupancy pattern for prediction purpose. In [85] a one-day experiment was conducted in three zones of a building to test MPC with PMV constraint.

An experimental research was conducted in one solar home during heating and cooling season. In this experiment local weather forecasting and occupancy presence predictions were used to minimize total energy use in this building. This study shows nonlinear model predictive control can results in 30% energy saving during two months heating season experiment and 17.8% energy saving during one week cooling season, in contrast with scheduled temperature set-points [20].

A fifty-one and ten day experiment was conducted in two commercial, which resulted in 19% and 32% energy-saving [21]. In this experiment, weather forecasting and energy price profile was considered to minimize CO_2 emission, overall cost, and occupants' discomfort level. The building LTI model has been tuned every 24 h with the new data from sensors and occupant discomfort model was tuned based on surveys on each person computer.

Stochastic model predictive control was tested in one student laboratory for four days. The SMPC was using RC validated model of the room. The optimization problem was running every 10 min for prediction horizon of 8 h to minimize energy cost. This study estimates 5–35% energy saving is achievable using SMPC with occupancy and weather prediction [93].

An experiment was conducted on high level MPC control of water-loop (chillers cooling towers, water pumps and thermal storage tank) to minimize the electricity bill of the HVAC system [140]. A prediction horizon of one day and sampling time of one hour were used in this study. Baseline and high-level MPC were put in contrast using electricity bills and coefficient of performance (COP) values. The results demonstrated 19.1% increase in COP using MPC [8]. The disturbances on the system and weather forecasting were assumed to be well known. In this research decentralized MPC was designed using sequential quadratic program (SQP) and dual decomposition. The computational effort for MPC and DMPC were put in contrast using MATLAB and IPOPT. The results showed significant reduction in computational efforts using DMPC [99].

5. Conclusions

This paper conducts a comprehensive review on occupancy-based model predictive control for building indoor climate mainly focusing on HVAC systems. In most studies, occupancy behavior, specifically, presence and numbering were captured through using PIR, Camera, door sensors, phone WI-FI, GPS, etc. By doing so, occupancy measurement can lead to less discomfort time in contrast with traditional schedule based controls. However, using measurements alone can lead to discomfort when the room is first being occupied, which makes using prediction necessary. An effective prediction of occupancy behavior will decrease discomfort and also save more energy through providing more time for HVAC systems to achieve its best performance. Furthermore, it can save further energy when the room is going to be unoccupied. All occupancy behavior models increase the need for an integrated platform of sensors and software, which turns out to be a new challenge in terms of cost and effectiveness. Model predictive control utilizes occupancy measurement and prediction to maximize user comfort while minimizing energy consumption. In general, comparing with rule-based controls, MPC based HVAC controls can achieve 10% more energy savings, and occupancy-based MPC can further save up to 30% more energy.

Table 4
Building model predictive control with occupancy data.

study	experimental	Simulation	Building HVAC Model	Building Type	HVAC Type	Occupancy	Control Method	Control variables	MPC time steps	MPC Prediction horizon	MPC objective	Optimization Method	Software	Study Duration and location	Methods Compared	Savings	Considerations	Related studies
[80]	N	Y	RC, Parameters chosen	commercial building, room-level climate control	VAV	Perfect Predictions & occupancy profiles	MPC & rule-based, with occupancy measurement	Airflow and temperature		30 and 120 min	Energy	BFGS	IPOPT Matlab	One day winter, spring, and summer Florida	conventional controller with schedule	10–48% MPCWinter: 43.4–48.2% MPC-spring: 28.3–38% MPCsummer: 28.3–38%	under-actuated HVAC zones, Weather prediction	[16]
[16]	Y	Y	RC Physics-based	commercial building one room UFL (Pugh Hall)	VAV	PIR	MPC & rule-based, with occupancy measurement	Flow rate and temperature of zone supply air			Energy		IPOPT Matlab	18 days	conventional baseline controller	Almost 40% For both controllers	zone-level control	[80,127]
[20]	Y	N	3R2C Estimated parameters	Solar House test-bed Pittsburgh, PA office	multi-split fan coil, HRFHS	Motion, CO_2, Acoustics, and lighting predictions 80% accuracy	NMPC	Temperature set-point	15 min	Heating season: 24 h Cooling season: 3 h	energy	dynamic programming	Matlab Simulink	Two months in the heating season, and a week in the cooling season	conventional controller with schedule	17.8% cooling season, 30.1% heating season saved energy	Adaptive Gaussian Process, Hidden Markov Model, Episode Discovery and Semi-Markov Model [129], local weather forecasting model	[129]
[19]	Y	Y	RC ODE parameters identified using nonlinear regression	student computing laboratory	single-stage heat pump (AC)	Estimate occupancy behavior using temperature	learning-based MPC Tune model based on new data	AC ON-OFF	15 min	5 h	Energy +weighted temperature error		Matlab SNOPT solver TOMLAB library	One day Berkeley	Two-position control	30%–70% saved energy		[130,131]
[82]	Y	N		commercial building	dual duct variable volume	PIR, CO_2, People counter, historical data	MPC	mixed-air temperature, supply mass flow hot and cold deck discharge air temperatures, zone supply temperature,		3 h	Utility cost	interior-point nonlinear programming solver	IPOPT	A week in February and October	rule-based schedules retrofitted direct digital control	energy saving: transition season: 20% Heating season:70% 10% peak power reduction		[14]

Table 4 (*Continued*)

study	experimental	Simulation	Building HVAC Model	Building Type	HVAC Type	Occupancy	Control Method	Control variables	MPC time steps	MPC Prediction horizon	MPC objective	Optimization Method	Software	Study Duration and location	Methods Compared	Savings	Considerations	Related studies
[67]	N	Y	EnergyPlus	Eight residential buildings	three-stage HVAC	motion and door sensors HMM	HMM probability +setback						EnergyPlus		reactive thermostat	28% energy saving		
[22]	N	Y	Linear	Single-zone building		Markov chain model	MPC	Input heating energy	1 h	24 h	Energy +occupancy	dynamic programming			baseline	44% energy	Off-line and on-line MPC	[78,87]
[78]	N	Y	RC	single-zone		Markov Chain model	MPC	Input heating energy	1 h	24 h	Energy use, set-point, occupancy				Compared to Scheduled occupancy	19% Energy		[22]
[87]			RC state-space			Moving Average Discomfort Density	MPC	Temperature set-point	15 min	1 h	Energy		CVX		smart reactive	12% Energy saving		
[81]	N	Y	RC	Single room		PMV, AMV	MPC, SMPC	Input heating energy	15 min	5 h	Energy				rule-based PI	Increased comfort level	Experimental thermal sensation model	[96]
[132]	Y	N	RC, Identified parameters	Four floor building	ceiling radiant	NAN	MPC	Supply water temperature	20 min	2 days	Energy	Quadratic programming	Scilab	January until March	Heating curve	16%–28%		
[21]	Y	N	Physics-based, Parameters identified every night	Commercial two office buildings 3-floor 3322 and 1808 square meter		Online tuned comfort model based on occupant feedback	MPC	Supply air temperature and flow	5 min		Running cost, PPD, CO_2 emissions	Quadratic programming		two winter months, Australia	baseline	19% and 32% Energy saving	survey	
[62]	Y	N	Linear, Identified model	1071 m2	fan-coil solar cooling	NAN	MPC	Temperature set-point, fan-coil speed			PMV, Temperature, Control signal			September, 2010 South East of Spain	Four different MPC configuration	–	Four different MPC configuration were studied	
[88]	N	Y	state-space model	Two-zone	AHU	Assumed to be Well known	Distributed MPC	Input energy	30 min	24 h	Utility cost, occupant discomfort	Dynamic programming		Indiana		Affine Quadratic Regulator was the fastest approach		
[63]	N	Y	linear	Office site	VAV	CO_2	MPC	Ventilation rate		90 min	States and Input	least-square	MATLAB	Sweden	Feedback, Open loop predictive controller	10 times Lower CO_2 set point error		
[83]	Y	N	RC and CO_2 model	laboratory room 80m2			MPC	Supply air temperature and flow	10 min	9 h	Energy	MPT, parametric programming	MATLAB	3 days Stockholm	Switching controller	31–33% Energy saving	randomized approach, scenario based	[133,134]
[17]	N	Y	RC	One zone	VAV	Known	MPC Occupancy setback	airflow and temperature set-points			Energy use		MATLAB	Florida Winter, Summer	Conventional	12–37% Energy saving	Uncertainties effect	

Table 4 (*Continued*)

study	experimental	Simulation	Building HVAC Model	Building Type	HVAC Type	Occupancy	Control Method	Control variables	MPC time steps	MPC Prediction horizon	MPC objective	Optimization Method	Software	Study Duration and location	Methods Compared	Savings	Considerations	Related studies
[84]	Y	N	RC	Four 60 m2 rooms		Known Meeting	MPC	Meeting location, airflow and temperature			Energy	MILP, LNS	Gurobi 5.6	5 summer days	Baseline	50–70% Energy saving		
[86]	Y		RC	Two buildings	VAV	Prediction	MPC	Temperature set-point		24 h	Cooling load, PPD		MATLAB TRNSYS SCADA	July–August 2013–14	Baseline	4–58% Energy saving		[85]
[89]	N	Y	RC physics	Single room office		Known	MPC	CO_2 level Temperature			Energy		MATLAB Simulink	12 h	Feedback controller	5–44% Energy		
[90]	N	Y	Physics based	Multi-zone 8 zonecommercial	VAV	CO_2, Estimator	MPC	Supply air temperature and flow	1 min	5 min	Energy IAQ PMV	GA	TRNSYS		conventional	12%		
[12]	N	Y		Three building, 10 zones		Known Schedule	MPC	Temperature set-point			Energy cost, PPD	Dynamic programming	EnergyPlus	3 day	Rule Based Controllers	12–22%	Microgrid, Solar, Battery, Wind	
[56]	N	Y	LTI	TRNSYS	TABS	Known	MPC PMV	Input heating energy	30 min	8–32 steps	Energy cost, PMV	Quadratic programming	TRNSYS Matlab		MPC without PMV	10–15%		
[79]	N	Y	Linear	single-zone building		Known	MPC PMV	Input heating energy		10 steps	Energy, Setpoints	quadratic programming		1 week	MPC	PMV-based control gives better results		
[54]	N	Y	EnergyPlus	Multi-zone		Known	MPC	Temperature Setpoint		24 h	Energy cost, PPD	GA	MATLAB EnergyPlus	Italy	Baseline	56% Energy		
[91]	N	Y	RC	Single Room	Water loop	Markov	SMPC	Input heating energy	1 min	1 h	Temperature set pint error, input, cost	quadratic programming			PI	38.3% discomfort reduction		
[92]	N	Y	Linear	Multi-zone 10 rooms		Predefined probability	SMPC DMPC	Input heating energy			Input heating energy cost, slack	Linear programming	MATLAB		PID		setback	
[103]	N	Y	3R2C		AC		SMPC				Energy				MPC	2%		
[93]	Y	N	RC	80m2 laboratory		Learn patterns	SMPC CO_2 SMPC	Supply air temperature and flow	10 min	8 h	Energy cost			4 days Stockholm	PI and switching	5–30%		

There are several challenges and open issues that were observed during literature review:

- **A reliable baseline building model:** Building energy consumption is a complex process involving fundamental heat transfer and thermodynamic process. It can be affected by many different factors including: weather condition, building characteristics, occupancy behavior, air conditioner unit, etc. Such process raises questions: (1) how to establish a reliable baseline model, so that the MPC design will achieve the expected energy savings? (2) how to have a perfect control oriented model so that the designed MPC has the best performance? The trade-off between data-driven and physics-based models always presents a challenge for researchers.
- **A more comprehensive and accurate occupancy behavior model:** There are many methods for occupancy modeling and events modeling – such as: occupancy presence, overtime works and meetings. Most of studies in occupancy-based model predictive control with occupancy prediction use only one event, such as occupancy presence or number of occupants, as the input to the controller design. However, in reality, different events have to be considered together for a building when centralized controller is being used. For example, an occupant enters room could trigger a series of event: presence and interactions (adjusting thermostat, turn on/off lights and others). Such process requires more complex models to represent a complete process of occupancy behavior. This will also increase the complexity of MPC control design.
- **Trade-off between complexity and performance:** Solving optimization problem for a complex system increases computational cost and memory demand. In other hand, using predictions of weather, occupancy and energy price bring stochastic nature to the problem. Complexity of such a problem increases the probability of local optimality and error, Which raise a question on how to find a trade-off between complexity and performance [141].

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