Market and Behavior driven Predictive Energy Management for Residential Buildings

Abstract

With the advancement of smart home and grid, a more connected and efficient operation of the grid is achievable. Involving buildings as the largest consumer of electricity in such a smart operation is a critical step in achieving an interactive grid system. In this paper, a building energy management system is introduced considering electricity price and people behavior, controlling major consumers of electricity in a single family residential building. An air conditioner, water heater, electric vehicle, and battery storages are controlled in a photovoltaic (PV) equipped building. A model predictive control is designed to minimize the operation cost considering system model, electricity price and people behavior patterns in each device control. Centralized and stand-alone configuration of MPC for building energy management is formulated and were put in contrast for time of use pricing (TOU), hourly pricing and five minutes pricing. Simulation results show that in real time five minutes pricing these methods can achieve 20% to 30% cost savings in different appliances, and 42% savings in overall electricity cost adding battery optimal control compared to traditional rule based control. Cost savings and peak shaving results demonstrate the capabilities of introduced price and behavior based control.

Keywords:

Model Predictive Control (MPC), Building to Grid Integration, Building energy management system, real time pricing, occupant behavior.

Nomenclature

	General Form
p_i	Electricity price at step i
P_i	Device electricity usage at step i
u_i	System input
m	Prediction horizon
dt	Time step
ω	Slack variable objective weight
ε_i	Free variable to relax temperature constraint
$x_{tolerance}$	States tolerable relaxation
f_P	Power consumption of the device function of its control action
	Air Conditioner
P_{AC}	AC average electricity consumption (watt)
x_{AC}^i	AC on and off status
T_{in}^i	Building indoor air temperature
T_{out}^i	Outside air temperature
LB_{AC}	Lowest temperature allowed on occupied periods.
UB_{AC}	Highest temperature allowed on occupied periods.
OC_i	Occupancy statues of the zone
k_{oc_AC}	Temperature relaxation on unoccupied periods
$\alpha_1, \alpha_2, \alpha_3, and\ \alpha_4$	Identified gains for indoor temperature changes
Q_{solar}	Solar thermal input
	Water Heater
T_{wh}^i	Average hot water temperature in the water heater tank
$\dot{m}$	Hot water usage mass flow
$P_{element}$	Water heater heating element power
K_{wh}	Thermal conductivity of the water heart tank to ambient
T_{amb}	Water heater surrounding air temperature
Q_m^i	Average electricity usage of the water heater from historical data
T_{LB}^i	Water heater average temperature lower boundary
T_v	Allowed average temperature changes
T_{set}	Hot water temperature set-point
T_{low}^i	Lowest allowed hot water temperature at step i
C_w	Water thermal capacity
C_{wh}	Water heater tank thermal capacity

	Electric Vehicle
t_i^c	Historical average connection time estimated from smart meter data
π_j^{use}	Probability of the electric vehicle charger use electricity according to smart meter historical data
π_{max}^{use}	The largest probability value (π^{use}) to remove dimensions
t_a	Connection time
t_D	Estimated disconnection time
S_{EV}^{init}	Initial EV state of charge at connection time
S_{EV}^{i}	Electric vehicle battery state of charge
$S_{LB\_EV}^{i+1}$	Electric vehicle designed SOC lower boundary
$S_{UB\_EV}^{i+1}$	Electric vehicle designed SOC upper boundary
Q_{EV}	Electric vehicle battery capacity
η_c η_d	Charger efficiency
P_C P_d	Charger power
	PV and Battery
P_G	Power flow from the grid
P_L	Power flow to the building load
P_{PV}	Power flow from the photovoltaic panel
P_{BI}	Power flow to the battery
P_R	Power flow to the rectifier
P_I	Power flow from the inverter
P_{BO}	Power flow from the battery
η_c	Battery charging efficiency
η_D	Battery discharging efficiency
η_{con}	Converter efficiency
η_I	Inverter efficiency
η_R	Rectifier efficiency
S_{Bat}^{i}	Battery state of charge at step i
$S_{\max\_B}$ $S_{\min\_B}$	Maximum and minimum allowed stated of charge
P_{Gmax} , P_{Gmin}	Grid maximum and minimum power flow
P_{Bmax}	Battery maximum power flow
P_{Rmax}	Rectifier maximum power flow
P_{Imax}	Inverter maximum power flow
d_I, d_B	Power flow direction for battery and inverter
Q_{BAt}	Battery capacity
A_{AC} , B_{AC}	Air conditioner MPC constraint and bound matrices
A_{EV} , B_{EV}	Electric vehicle MPC constraint and bound matrices
A_{WH} , B_{WH}	Water heater MPC constraint and bound matrices
A_{Bat} , B_{Bat}	Battery MPC constraint and bound matrices
X_{AC} , X_{EV} , X_{WH} , X_{Bat}	Air conditioner, electric vehicle, water heater, and battery decision variables
a_1 , a_2 , a_3	Building load relation with other appliances decision variables

1 Introduction

Buildings, as the major electricity consumers globally, play an important role in shaping cities electricity generation, distribution and consumption and reducing greenhouse emission [1]. To make energy consumption of a city more efficient and sustainable, building energy management systems should be designed which can respond to the electricity grid conditions. However, involving buildings in the grid operation is a challenge, due to current inelastic buildings' electricity consumption and stochastic people behavior. This involvement requires buildings to have a flexible demand, where their electricity usage can change in response to economic signals [2]. For this purpose, many utility operators have designed demand response programs. These demand response (DR) signals, include incentive based programs and price based programs [3-5]. However, all these signals can be transformed into a dynamic electricity rate for buildings. Some popular pricing methods for DR are: time of use (TOU), critical peak pricing (CPP), extreme day pricing (EDP), and real-time pricing (RTP). The main difference of these pricing schemes is the level and frequency of price changes, which depends on the ability of the user to shift its consumption. Since most buildings are not capable of automatically respond to these price changes, DR pricing events happen less frequent than the actual price changes in the electricity market, which causes a gap between the producer and the consumer. In an ideal situation, buildings are charged a real-time cost of producing and distributing electricity and respond to its changes. Or, they can participate in the electricity market and negotiate for its price by placing bid and offer. However, such a load control should not interfere with people satisfaction in using their appliances.

Building consumption load is directly related to occupancy and number of people in a building. On the other hand, the objective of providing comfort and services makes people behavior modeling an important factor [6-8]. This consideration can result in more savings in some appliances consumption. There are many studies showing that considering occupancy presence in HVAC control system can save up to 23% [9, 10] in cost. This saving in HVAC operation mostly is achieved by relaxing temperature set point during unoccupied periods. Beside this, ASHRAE standard relates ventilation rate of each conditioned zone to the number of people in it, and the lack of an occupancy based thermostat control has led to maximum capacity ventilation designs, causing a large energy waste. Beside HVAC, lighting, appliances, water heater, PV battery and electric vehicle can be controlled considering occupants' behavior in their operation. There are many studies on optimally schedule appliances operation using input from the occupants, and showed benefit of such an input [11]. However, there are not many studies trying to use behavior patterns and occupancy models to avoid the extra input from the occupants. To automate such a scheduling method, a reliable occupancy behavior consideration is required.

This study is trying to close the gap between occupancy behavior and appliances scheduling method in different DR signals, by addressing these research questions:

- How does occupant's behavior affect appliances optimal control?
- Which pricing scheme is more effective in an optimal residential building energy management system?
- How to include residential battery energy management system for appliance control?
- What is the difference between centralized and stand-alone home appliances predictive control?

This paper introduces a price and behavior driven building energy management system (BEMS) using model predictive control(MPC). In this paper major residential appliances are controlled using both stand-alone and centralized MPC configuration. These appliances are residential air conditioner, water heater, electric vehicle, and battery. Three different pricing, namely TOU [12], day ahead hourly (DAP) [13] and whole sale five minutes [14] price, are used for performance evaluation. The main contribution of this paper is introducing occupant's behavior, extracted from smart meter data, into all levels of appliances control and introducing two methods of combining individual MPC controllers to achieve a better overall building performance. This method can be used in smart home energy management system where appliances are wireless enabled and can share information. The following figure (Figure 1) depicts the overall configuration of the proposed smart building control, where smart meter data is used to extract people behavior and used in different appliances to achieve a responsive load.

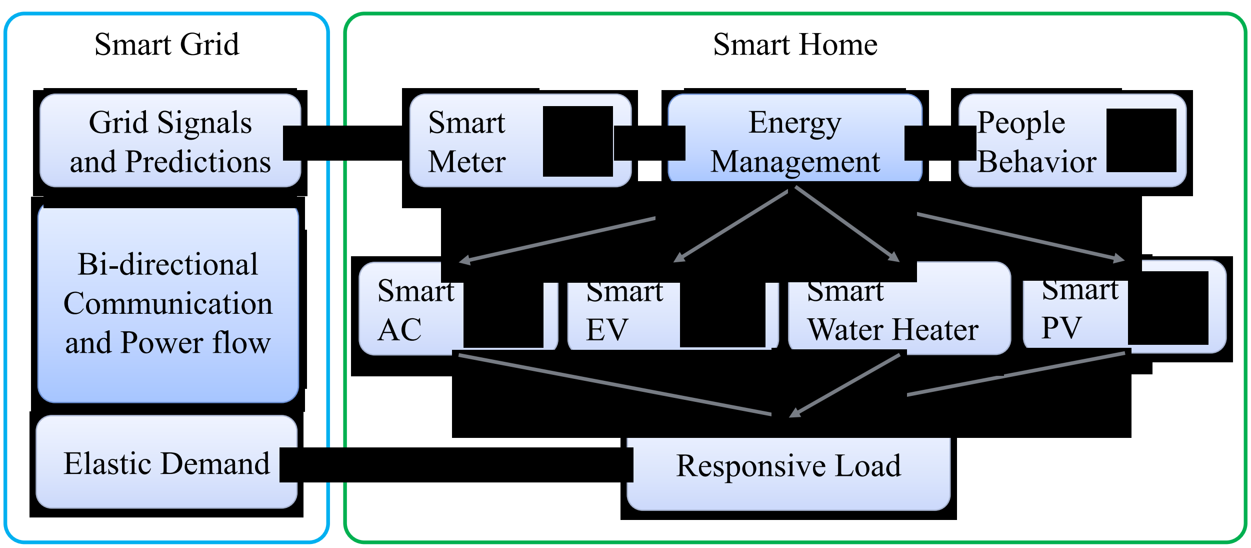

Figure 1: Overview of smart building to smart grid integration

This paper is organized as follow: Firstly, a comprehensive literature review is conducted and discussed. Secondly, the control methodology used for air conditioner, water heater, and electric vehicle, stand-alone battery MPC and centralized MPC are described. Finally, the simulation results are presented and discussed.

2 Literature Review

Building energy management system (BEMS) in literature refers to systems which are designed for monitoring, scheduling and controlling of appliances. A survey on building energy management systems has categorized them based on their control methodology, which are optimization based BEMS, and schedule based BEMS [15]. Both methods are trying to shift in-building consumers' operation to a later time when it is more efficient. In this paper, we use model predictive control (MPC) to find the optimal control action for in-building devices, which fits in optimization based BEMS category. The use of MPC in controlling individual devices such as EV, and HVAC started to get attention of researchers in the past ten years. Most researches in this area are focused on HVAC control, as heating, cooling, and air conditioning are high energy demanding activities.

2.1 Individual appliances model predictive control

HVAC as the largest consumer of electricity in buildings has been the subject of many research studies for many years[16-20]. Air conditioner control is tied up with building thermal model, which brings non-linearity, and different disturbances into the model based control. To deal with this complexity, metaheuristic optimization methods with a detailed EnergyPlus model is used in [21]. Such a model demands large computational resources, which can be reduced to a practical run time using a minimum reliable run period [21]. On the other hand, mathematical programming methods with a reliable linear model can achieve optimality with less computational effort [22]. Occupancy presence has been used for HVAC control in many research studies due to its impact on energy savings [18, 23-25]. Markov chain has been used widely for occupancy prediction in MPC implementations [26-28]. On the other hand, Predicted Mean Vote (PMV) method has been used extensively to introduce people comfort into HVAC control problem [18]. In [29] MPC using occupancy prediction and estimation is put in contrast in an experimental test. The results of this research show capabilities of MPC in utilizing either an estimated occupancy behavior using common available sensors (PIR, temperature and CO_2) or dedicated sensors such as 3D stereo vision camera with slightly better performance. In [30] occupancy presence pattern extracted from building monitoring data is used for an occupancy based MPC control in a multi-family residential building. In [31] advanced machine learning algorithms (Hidden Markov Model) are used to predict occupancy presence for a MPC controlled HVAC system, resulting in 30% energy savings in heating season in a one month experimental test. In [32] effectiveness of a HVAC control for grid integration is studied using MPC to maintain occupants' comfort while minimizing operation costs in different electricity tariffs. In [33] three model predictive control configurations are put in n contrast in an experimental setup to control HVAC and battery in a PV equipped building with the objective of maximizing comfort while minimizing cost in a dynamic price environment. These MPC configurations are, simplified thermal model with dynamic programming, simplified model with genetic algorithm and EnergyPlus model with genetic algorithm. Savings results show small difference implementing these three configurations. In [34] MPC is used to control room temperature set-points considering people comfort level to minimize HVAC operating cost. In their study nonlinear MPC is solved using genetic algorithm in

MATLAB coupled with EnergyPlus for building thermal simulations, and people comfort criteria is introduced to the system with occupant's input.

Vehicle to grid (V2G) concept discusses how to utilize electric vehicle battery as a distributed energy storage for a more efficient grid operation [35]. V2G integration studies can be categorized into bidirectional and unidirectional groups, where EV has a bidirectional [36] or unidirectional [37] power flow with the grid. Many configurations have been proposed for V2G MPC control, with control objectives of minimizing grid operation cost, loss, and emission or maximizing vehicle owner revenue, grid performance and reliability [38]. In [39] a model predictive approach is used for peak shaving and grid cost reduction, considering charging behavior predictions using linear regression and mean estimation. There are not many studies considering peoples' behavior in EV charging scheduling. However, this input is of great importance, as it effects EV consumption shifting capability and user satisfaction [40].

On the other hand, battery management research is tied up with renewable integration and distributed generation [41]. In [42] MPC based battery management system is designed for a photovoltaic panels (PV) equipped residential building. In their study, a second-life battery nonlinear model has been used with artificial neural network building load forecasting to minimize electricity cost and carbon emission. In a similar study MPC based battery management is used alongside appliances MPC control for a better load management using neural network (NN) for building load predictions [43]. Building load prediction is a necessary input to MPC problem for battery management, which is a challenge in residential buildings. In this study, we introduce two methods of MPC controller integration to overcome this challenge.

Despite the fact that water heaters are responsible for about 18% electricity use [44] and they are capable of shifting their consumption effectively, they have not been the subject of many research studies compared to EV, HVAC, and battery. In [45] water heater with storage tank is controlled using MPC to improve owner's benefit from self-consumption tariff in a PV equipped building. In [46] water heater optimal scheduling problem is studied controlling its set-point and its ON/OFF schedule in a day ahead dynamic pricing environment. In their study Dijkstra's algorithm is used to find control actions which resulted in 23% - 29% savings. In another study, multiple water heaters in residential sector are controlled using the MPC method to provide reserve services for renewable generation [47]. However, more research is needed to be done on this subject.

2.2 MPC based building energy management system

Distributed nature of building control motivates the BEMS design to be a distributed control. Hence, this is the subject of many research studies [48-51]. In a multi agent building energy management, each in-building device has its own control algorithm and it uses information from other devices or a central management system to achieve an overall optimal operation. The total operation stability and efficiency can be measured and simulated using game theory. In [52] a multi agent operation control of a HVAC system in a commercial building is proposed for a near optimal operation. Beside in-building distributed control, a cluster of smart buildings can be studied as a multi agent system. In [53] simulations for a cluster of smart buildings with PV and automated demand response show that the joint operation of smart buildings can achieve about 4.6% cost saving in a smart grid. In [54] optimal scheduling problem for shiftable appliances is solved using MILP for four different buildings with different usage patterns for comparison with the objective of reducing peak load resulted in 11% - 48% peak load shaving. All these multi agent designs are aiming to solve a problem which is too big to solve in a centralized configuration.

In [55] an agent based BEMS is designed controlling heat pump, washing machine, dryer, and dishwasher considering PV generation, building load model, and hourly dynamic pricing. Then this BEMS is simulated in an aggregated 200 households to simulate capabilities of such a system in peak shaving [56]. In [57] a building energy management solution is introduced controlling air conditioner, water heater, and electric vehicle using MPC. This BEMS framework is programmed in VOLTTRON platform in a later study with the same group [58]. BEMS in [3] is designed to control thermal and electrical load using HVAC, EV, and appliances considering demand response signal (TOU), PV production and Vehicle to grid (V2G) concept resulting in 28% to 40% savings. This paper represents detailed mathematical formulation for such a problem with multi objective optimization scheme considering, cost, energy, emission and comfort as objectives. In [59] an experimental study is conducted on a small residential home equipped with PV, battery, and solar collector testing price based MPC. In [60] the MPC based BEMS is studied for appliances with different deferable time scales in hour-scale and day-scale time steps. In their study an electric vehicle, PV, battery and local diesel generator is controlled considering stochastic behavior of PV generation in a mixed integer nonlinear programing. In [61] fifteen in building schedulable appliances including washing machine, air cleaner, lights, blinds, and, dryer are controlled in an integer linear programming problem in a real time pricing scheme resulting in 13% - 22% cost savings. In [62] schedulable appliances load, Electric vehicle, local generation and battery are simulated in a building, and the linearized model is used to control these devices in a TOU tariff. In [63] MPC performance under forecast uncertainties has been studied comparing stochastic MPC and deterministic MPC in a home equipped with heat pump, PV panel, battery, and fuel cell.

Results of this paper shows that deterministic MPC can achieve acceptable results and uncertainty from weather forecasting is neglected. In [64] a behavior based MPC is designed for delay flexible appliances and HVAC system resulting in a considerable cost savings in hourly day ahead pricing (DAP).

Table 1: Recent studies on MPC based building energy management systems for residential buildings

Study				Controlled devices						Grid signal		
Ref	year	Behavior based	MPC	HVAC	WH	PV	Battery	EV	Appliances	TOU	RTP	Hourly
[55, 56]	2013		Centralized	x		x			x			x
[5]	2014		Centralized	x					x			x
[3]	2015		Centralized	x		x		x	x	x		
[65]	2015		Centralized	x	x		x		x			x
[64]	2016	x	Standalone	x					x	x		x
[66]	2016		Standalone	x		x	x					x
[28]	2016	x	x	x								x
[67]	2017		x	x						x	x	x
[59]	2017		Centralized	x		x	x			x		
This Study	**2017**	**x**	**Centralized and Standalone**	**x**	**x**	**x**	**x**	**x**		**x**	**x**	**x**

In summary, numerous prior research studies focus on centralized or standalone control design of one or a few individual home appliances, considering one or more demand response or electricity pricing schemas, as summarized in Table 1. Specifically, a recent review paper on home energy management system shows that 25 research papers using dynamic pricing reported an average cost reduction of 23.1% and 19 research papers reported an average peak reduction of 29.6% [68]. However, most of these studies do not consider how occupant behavior, often the leading energy consumption factor in residential buildings, can be integrated into the home energy management system. However, a simple occupant presence based thermostat control has demonstrated up to

22% energy savings [69]. The challenges to include occupant behavior into residential energy management system design are:

1) Sensing and data acquisition: adding addition sensors in a residential building is extremely difficult and often not possible due to privacy issues. Thus, the actual usage of an energy consumer device is often unknown, which is a challenge to the residential appliance control design.
2) Feature extraction from usage patterns: with the development of smart meters, rich data sets are available to derive occupant energy usage patterns. What are the important features from those patterns and how to integrate those features into the control design is still a question.

In this study, a novel behavior and price based model predictive control (MPC) is first introduced for individual appliances including air-conditioning, water heater, electrical vehicle (EV) and battery energy storage system (BESS) for smart homes. The control design considers both centralized and individual MPC approaches. Specifically, we develop a control algorithm to operate the water heater at the minimum energy usage based on historic usage patterns without knowing the future water heater usage schedules. In addition, we estimate the occupant arrival and departure time of EV based on the historic probability distribution of EV usage. Furthermore, we design a centralized MPC considering all different energy consumer devices in a smart home with PV generation and battery energy storage system. Hence, the novelty of this paper is on the design and modelling of occupant behavior based MPC for residential buildings in a holistic and systematic perspective, and the comparison of energy cost savings based on various utility pricing schemas to the current of state.

3 Research Approach

3.1 Description of case study

A residential building from Pecan Street Inc. database is selected as the case study [70]. This building is equipped with 2.2 kW solar photovoltaic panels. The electric vehicle has a battery size of 34 kWh with 3.3 kW charging power. The water heater has a tank size of 100 liters and has maximum 2500W heating power. During the simulation, we added a battery size of a 5kWh with charging and discharging efficiencies of 0.95 and rectifier and inverter efficiencies of 0.95. The EV battery charging has an efficiency of 0.9. Smart meter data is from Pecan Street data sets with 5 minutes interval. The initial EV SOC at arrival, people hot water usage, and PV generation are extracted from smart meter data. We assume a maximum charging and discharging power of 1 kW for the PV battery and maximum allowable grid injected power of 8 kW.

3.2 Behavior patterns and feature extraction

3.2.1 Water Heater

Behavior patterns

Figure 2 shows the two years of hourly water heater usage pattern from Monday to Sunday for the selected residential buildings of Pecan Street Inc. Specifically, Figure 2 a) shows the probability of the water heater electricity usage in each hour of the day and Figure 2 b) shows the hourly average energy consumed by the water heater. Figure 2 clearly shows that the water heater usage has three peaks: early morning, evening and late night. Besides these three peaks, water heaters try to maintain the temperature set-point most of the time. Hence, it is important and necessary to consider such occupant behavior in control design to maximize the consumption shifting capability while providing enough hot water.

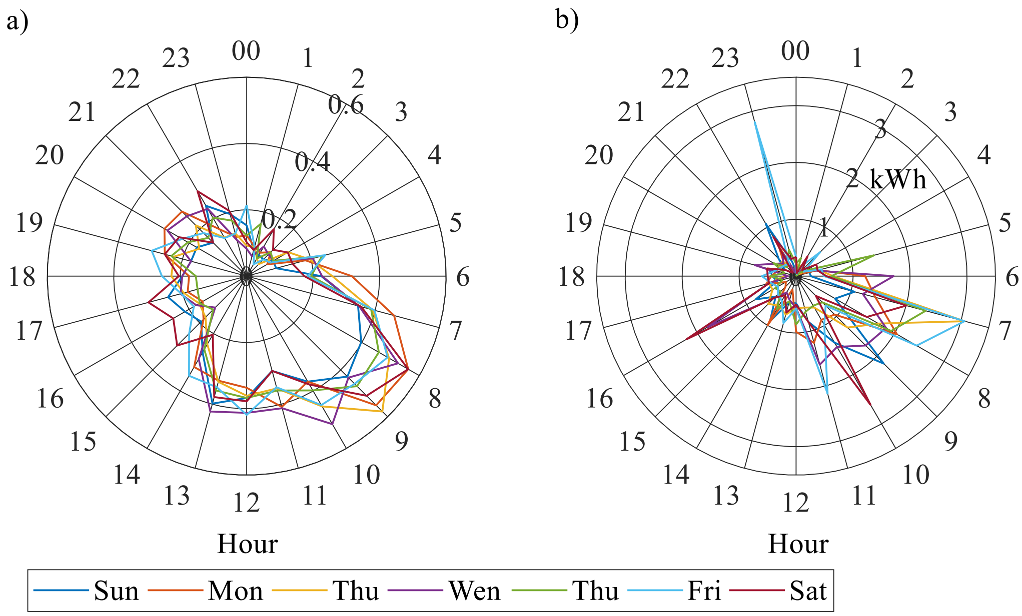

Figure 2: Water heater usage pattern for 122 homes: a) probability of water heater electricity usage in each hour of the day, b) average hourly energy consumed by the water heater

Behavior feature extraction for controls

Since major energy consumption of the water heater is related to hot water usage and not the energy losses, reheating energy consumption mostly happens after a major hot water usage such as shower. After this major hot water usage, the mean water temperature in the tank drops significantly. However, the output hot water has the set-point temperature as the water in the tank mixes slowly. The water heater controller should add just enough heating energy into the water heater tank so that it is never cold. This is where the historical water heater usage patterns are used in this intelligent control. We develop a new design for the lower bound of tank water temperature to save energy. This lower bound increase with a rate that the total heating energy added to the tank is larger or equal to the historical average energy drawn from the tank in each hour of a day. Figure 3 shows the detailed algorithm. Lower bound temperature is designed to increase from current water temperature to lower set-point dead band (T_{set}- $T_v/2$) with a rate equal to average water heater energy use if it is in use. However, the tank maintains a safety temperature threshold of 40°C. This threshold is due to the fact that average historic energy consumption of water heater is defining the amount of energy added to the water. If we assume the input cold water to the tank is about 20°C and the output hot water is about 60°C, then MPC is utilizing only half of the tank $(60-40)/(60-20)$ energy storage. However, this does not mean that MPC will utilize only half of the energy consumption shifting capabilities, because the extracted energy due to hot water use is not always more than this threshold.

if $T_{wh} > T_{set}\text{-}\, T_v/2$
    $T_{LB}^{i} = T_{set}\text{-}\, T_v/2$
else if $T_{wh} < T_{set}\text{-}\, T_v/2$
    if $T_{wh} < T_{LB}^{i-1}$
        if $T_{wh} > 40°\mathrm{C}$
            $T_{LB}^{i} = T_{wh}$
        else if $T_{wh} < 40°\mathrm{C}$
            $T_{LB}^{i} = 40°\mathrm{C}$
        end
    else if $T_{wh} > T_{LB}^{i-1}$
        if $T_{LB}^{i} < (T_{set} - T_v)/2$
            $T_{LB}^{i} = T_{LB}^{i-1} + (Q_m^i)/C_{wh}$
        else if $T_{LB}^{i} > (T_{set} - T_v)/2$
            $T_{LB}^{i} = (T_{set} - T_v)/2$
end **end** **end**

Figure 3: Water heater temperature lower bound design logic

3.2.2 EV Behavior

Behavior patterns

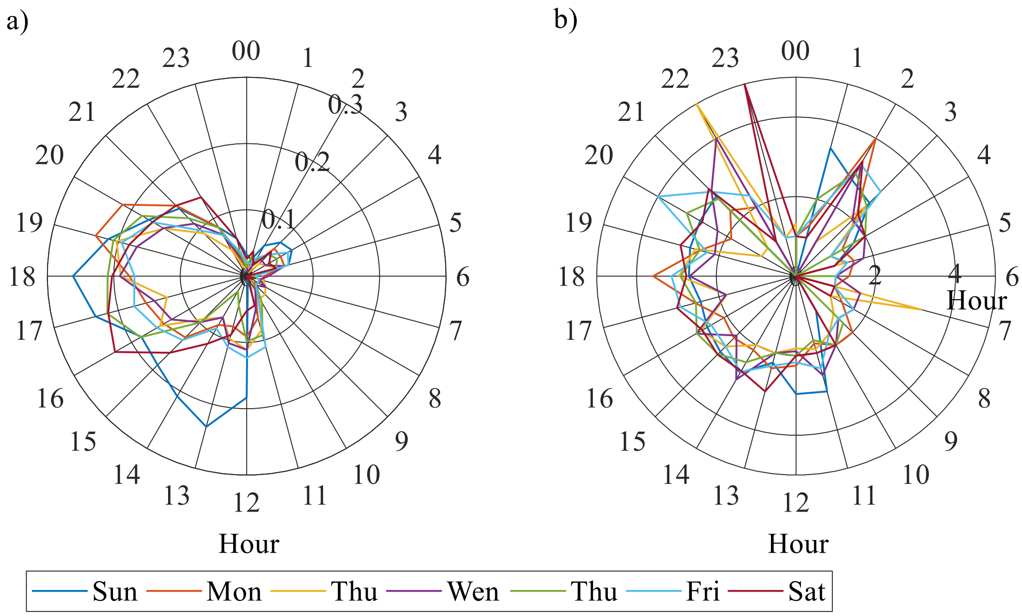

Figure 4: EV charger behavior patterns from Monday to Sunday: a) probability of the charger electricity usage in each hour of the day, b) average charging duration of each plug-in hour

Figure 4 a) shows the probability of the charger electricity usage in each hour of the day based 2 years data. For this particular house, the EV has a high probability of charging between 5pm and 7pm for weekdays and between 1pm to 6pm for weekends. Figure 4 b) shows the average charging duration of each plug-in hour. Depending on what time the EV is plugged in, the charging duration is between 0.5 to 5 hours. Most of the time, the charging duration is around 3 hours if the EV is plugged in between 11am to 8pm.

Behavior feature extraction for controls

Smart meter data of EV electricity consumption in the selected building is used to capture EV arrival time. In order to schedule EV charging, departure time should be known or accurately estimated. This estimation of departure time is important to make sure that the EV is fully charged before it departs while minimizing the charging cost. One potential approach is to estimate this departure time using historical data for departure time and build up a cumulative probability for every arrival time and pick a departure time through a random sampling. However, in this study, we developed an algorithm based on EV usage patterns presented in Figure 4. It is designed with the assumption that the departure happens sometime between arrival and twice of the historical average charging duration as shown in Figure 5.

For $n = 1 \ to \ n_m = (t_i^c)/dt$

$\pi(EV\ stay\ Connected\ until\ n+i) = 1 - \frac{1}{n_m}\sum_1^n\left(1 - \frac{\pi_{n+i}^{use}}{\pi_{max}^{use}}\right)$

IF $rand(n) < \pi(n+i)$:

$t_D = Time(i+n)$

End

IF $no\ t_D\ was\ found$:

$t_D = t_i^c$

Figure 5: Electric vehicle departure time estimation

After estimating a departure time, A lower bound is designed for the EV SOC to limit the lowest allowed SOC in a way that EV is charged before the estimated departure time. The EV starts charging if the SOC is below 40%. Figure 6 describes the logic on how the lower bound is designed. Then this lower bound is fed to the MPC problem.

if $S_{EV}^i < 40\%$

$S_{LB\_EV}^i = 40\%$

else if $90\% > S_{EV}^i > 40\%$

$$S_{LB\_EV}^i(j) = S_{LB\_EV}^{i-1} + \frac{\left(90 - S_{EV}^{init}\right)}{(t_D - t_a)} \times dt$$

else if $S_{EV}^i \geq 90\%$

$S_{LB}^i = 90\%$

Figure 6: Electric vehicle SOC lower bound design

3.3 Standalone Model Predictive Control Design

Model predictive control (MPC) is a controller design which use system model to predict future states of the system and pick a set of control actions that optimize an objective function [71]. The general form of the MPC problem used in this study is presented in the following formulation. The objective function includes two parts: cost of operation, and cost of constraint relaxation. Linear models are used for the MPC formulation to take advantage of fast mathematical programming algorithms to solve the problem [10]. It should be mentioned that MPC is fairly robust to disturbances and modeling errors [72]. Usually system duties are defined in the MPC constraint to insure they are satisfied. These constraints are state of charge boundaries in battery and EV control, and temperature limits in water heater and AC control.

$$\min \sum_{i=1}^{m} p_i P_i dt + \omega \varepsilon_i \tag{1}$$

Subject to:

$$LB - \varepsilon_i < X_{in}^{i+1} < UB + \varepsilon_i$$

$$\mathrm{x}^{n+1} = \mathrm{A}\mathrm{x}^{n} + Bu$$

$$P_i = f_P(u)$$

$$u_i \in U \quad \varepsilon_i \in \mathbb{R}_{\geq 0}$$

Beside the operation cost in the objective function, there is a weighted free variable which is designed to relax constraints to avoid infeasibility. All designed free and decision variable weights have the same unit. This is how the relaxing variable works. When system states are outside the designed boundaries and the system physically is not able to move the states back to the designed boundaries in one control step (for example, when indoor temperature is not in the comfort zone and the AC is not able to move it back to the comfort zone in just one control horizon step), then the free variable (s) which is designed to relax the constraint will increase, which results in a grow in penalty cost on the objective function. This penalty cost has a large value when the boundary violation is considerable. If the boundary violation is very small (smaller than the designed tolerable violation in free variable gain design ω), then the system will relax the constraint slightly to avoid an unnecessary control action. Hence, as long as the cost of relaxing the constraints is greater than the cost of operating the device (considerable boundary violation), the optimization result is to turn on the device.

3.3.1 Air conditioning

In order to separate simulation model from the model used for model predictive control and nonlinearities, an online estimation method is used to estimate building thermal behavior in every step of control using historical data available from previous simulation steps. Gains of a linear model relating indoor temperature changes to previous switching control actions, outdoor and indoor temperature difference, and solar radiation, are estimated solving a least squared error problem.

$$\dot{T}_{\text{in}} = (x_{AC}) \times \alpha_1 + (T_{\text{out}} - T_{\text{in}}) \times \alpha_2 + (Q_{\text{solar}}) \times \alpha_3 + \alpha_4 \tag{2}$$

For this estimation 20 steps of historical data, which is 100 minutes, have been used. Estimation error has been measured in degree Celsius by calculating the difference between estimated temperature in previous step of the simulation and the actual resulted temperature for the current step of simulation. Simulation results show that increasing estimation steps more than 20 steps won't increase the accuracy of gain estimations significantly. This model simply fit a linear model to the latest thermal behavior of the building, and its projection is used for the predictive control. Simulated building thermal model is a resistance capacitance (RC) network model verified with AC load in a residential building [73]. This error has a mean value of zero and variance of 0.01°C for one step (five minutes ahead) modeling in a one-year simulation test.

In this study, a residential unitary air to air heat pump is used as the air conditioner using coefficient of performance to calculate AC thermal load and an energy input ratio curve to relate AC performance to indoor and outdoor temperatures [73]. MPC problem for the AC control is designed to minimize operation cost of AC while maintaining indoor temperature. The constraint on the temperature is for ±1.5°C when the building is not occupied. The decision variable for the optimization problem is a binary (ON/OFF) decision. The problem is solved with a prediction horizon of one hour, at five minutes step. One hour is chosen because simulation results for a longer prediction horizon does not show significant cost savings changes. The temperature constraint relaxation tolerance for the AC is considered to be 0.1°C resulting in $\omega = abs(p_i)P_{AC}dt/0.1$. The overall MPC problem is formulated as below:

$$\min \sum_{i=1}^{m} p_i P_{AC} x_{AC}^i dt + \omega_{AC} \varepsilon_{AC}^i$$

(3)

Subject to:

$$LB_{AC} - k_{oc\_AC} \times (1 - OC_i) - \varepsilon_{AC}^i < T_{in}^{i+1} < UB_{AC} + k_{oc\_AC} \times (1 - OC_i) + \varepsilon_{AC}^i$$
$$T_{in}^{i+1} = T_{in}^i + \left(x_{AC}^i\right) \times \alpha_1 + \left(T_{out}^i - T_{in}^i\right) \times \alpha_2 + \left(Q_{\text{solar}}\right) \times \alpha_3 + \alpha_4$$

$x_i \in \{0,1\} \quad \varepsilon_i \in \mathbb{R}_{\geq 0}$

3.3.2 Water heater

Water heaters are responsible for almost 18% energy consumption in buildings [44]. Prior studies try to utilize water heater storage tank to respond to demand response programs [74, 75]. However, to the best of author's knowledge, none of them consider occupant behavior in their controls, and a few of them are studied in an integrated control with other appliances [65]. The MPC problem for the water heater follows the same general format in Eq. (1). This problem is to minimize the operation cost while maintaining average water tank temperature. The MPC problem has been solved for a prediction horizon of four hours for every five minutes. The model used in the MPC problem is a one-node linear water heater model derived from energy balance principals. The temperature constraint relaxation tolerance for the water heater is considered to be 0.5°C resulting to $\omega = abs(p_i)P_{element}dt/0.5$.

$$\min \sum_{i=1}^{m} p_i P_{element} x_i dt + \omega_{wh} \varepsilon_{wh}^{i}$$

Subject to:

$$T_{LB}^{i} - \varepsilon_i < T_{wh}^{i+1} < T_{UB}^{i} + \varepsilon_i \tag{4}$$

$$T_{wh}^{i+1} = T_{wh}^{i} + \frac{P_{element}}{C_{wh}} x_i dt - \frac{\dot{m}C_w}{C_{wh}} \left(T_{wh}^{i} - T_{amb}\right) dt - \frac{K_{wh}}{C_{wh}} \left(T_{wh}^{i} - T_{amb}\right) dt$$

$$x_i \in \{0,1\} \quad \varepsilon_i \in \mathbb{R}_{\geq 0}$$

3.3.3 Electric vehicle

Previous research studies focus on utilizing electric vehicle battery for demand response programs under vehicle to grid (V2G) concept [76]. In most of these studies, model predictive control is used for price based EV battery management in individual EV charging problem or fleet of EVs in linear and nonlinear configurations. A linear model is used so that a fast mixed integer linear programming (MILP) optimization solver can be used. The SOC constraint relaxation tolerance for the EV is considered to be 1% resulting in $\omega = abs(p_i)P_C dt/1$. EV is modeled with a battery size of 34 kWh and residential charger of 3.3 kW. Five hours prediction horizon is chosen with respect to average connection time of four hours. The choice of prediction horizon highly depends on the capability of the device to shift its consumption and existence of lower prices in further periods. The following equation formulates the MPC control design for the EV:

$$\min \sum_{i=1}^{m} p_i P_C x_i dt + \omega_{EV} \varepsilon_{EV}^{i}$$

Subject to:

$$S_{LB\_EV}^{i+1} - \varepsilon_i < S_{EV}^{i+1} < S_{UB\_EV}^{i+1} + \varepsilon_i \tag{5}$$

$$S_{EV}^{i+1} = S_{EV}^{i} + \frac{\mathrm{dt}}{Q_{EV}}(\eta_c P_C x_i - \eta_d P_d)$$

$$x_i \in \{0,1\} \quad \varepsilon_i \in \mathbb{R}_{\geq 0}$$

3.3.4 Stand-alone MPC Design with BESS

In many practices building load can only be powered up by either the grid or inverter output and the grid does not accept negative load. However, this is not the most efficient configuration. In order to benefit from feed-in-tariff and utilize the battery to respond to grid signals, power flow is designed bidirectional in this study between building and the grid as shown in Figure 7. The PV generation data is from measured data of the selected building. The converter, inverter, and rectifier are modeled with a constant efficiency, and power flow directions are chosen as a free variable to avoid nonlinearity caused by the flow direction. This brings two extra decision variables to the problem.

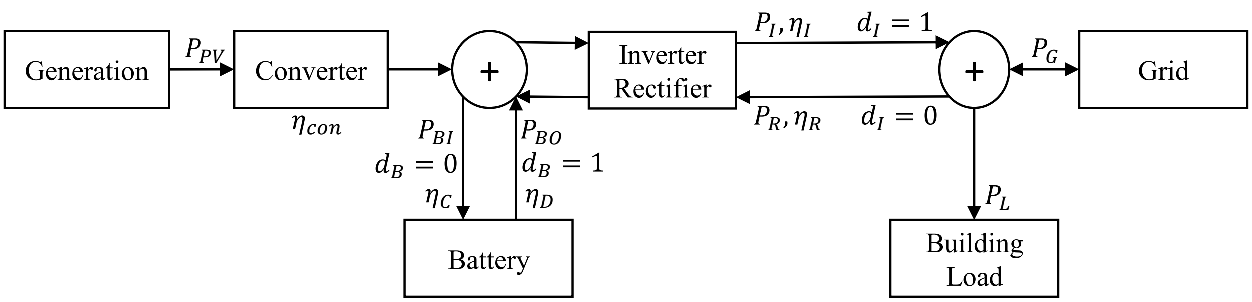

Figure 7: Overview of building-to-grid power flow with PV and Battery

The MPC problem for a battery energy storage system is designed to minimize the building operation cost. Two power balance equations are used as constraints for the following two points in the system. One is where the battery is connected with the converter and inverter and the other is where the inverter, building and grid are connected. Other constraints include: the maximum and minimum power flows and battery state of charge limits. A free variable is used to relax SOC constraint to avoid infeasibility with constraint relaxation tolerance of 0.1 resulting to $\omega = abs(p_i)P_{Bmax}dt/0.1$. Finally, constraints on P_I, P_O, P_{BO} and P_{BI} limit power flows to be on one direction depending on d_I and d_B free variables.

$$\min \sum_{i=1}^{m} p_i P_G^i dt + \omega_{Bat}\varepsilon_{Bat}^i \tag{6}$$

Subject to:

$$P_G = P_L + P_R - P_I$$

$$P_{PV}\eta_{con} = P_{BI} - P_{BO} + {}^{P_I}/_{\eta_I} - \eta_R P_R$$

$$
\begin{aligned}
&S_{Bat}^{i+1} = S_{Bat}^{i} + \frac{\mathrm{dt}}{Q_{Bat}}\left(\eta_C P_{BI} - {}^{1}\!/_{\eta_D}\, P_{BO}\right)\\
&90 - \varepsilon_i < S_{Bat}^{i+1} < 20 + \varepsilon_i\\
&P_{Gmin} \leq P_G \leq P_{Gmax}\\
&0 \leq {}^{P_I}\!/_{P_{Imax}} \leq d_I\\
&0 \leq {}^{P_O}\!/_{P_{Rmax}} \leq 1 - d_I\\
&0 \leq {}^{P_{BO}}\!/_{P_{Bmax}} \leq d_B\\
&0 \leq {}^{P_{BI}}\!/_{P_{Bmax}} \leq 1 - d_B\\
&\\
&d_I, d_B \in \{0,1\} \quad P_{BI}, P_{BO}, P_I, \varepsilon_i \in \mathbb{R}_{\geq 0}
\end{aligned}
$$

This MPC is solved using MILP to find optimal battery operation based on load and PV generation predictions. PV generation prediction is derived from weather data. However, residential building load prediction is a challenge due to its highly stochastic behavior. In order to estimate future load of the building, MPC solutions of other appliances in each step of the control are summed up as shown in Figure 8. MPC output of each device at each step is a sequence of control actions that optimizes its objective function.

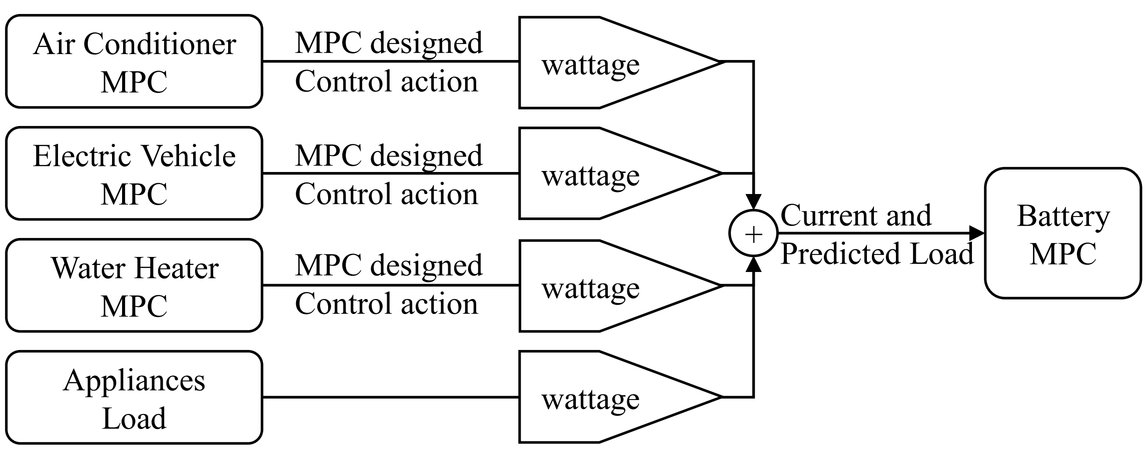

Figure 8: Overview of standalone MPC configuration

The MPC problem is solved for a prediction horizon of eight hours with five minutes time interval. The battery MPC problem could have a long prediction horizon in order to respond to daily price changes happen in high peak and low peak periods. In general, each high, mid, and low peak prices happen in one third of the day. To make the MPC problem to see future lower prices in a day, at least eight hours of prediction is needed. In order to, test this hypothesis, different prediction horizons are tested for one day simulation. It is observed that control actions for battery control does not change for any prediction horizon longer than eight hours.

3.3 Centralized MPC Design for Integrated Systems with BESS

In an ideal situation, there would be a controller which is aware of all devices models, and disturbances predictions. This ideal scenario is configured as a centralized controller, where one MPC controller produces control actions for all connected devices. To design such a controller, the whole building has been modeled as one system to reduce building operation cost. In this system, control actions include: the AC on/off, water heater on/off, EV on/off , and the battery charge and discharge decisions. The system model includes: the AC and building thermal model, EV battery model, water heater model, and battery and PV model. Disturbances to such a system would be, ambient weather, solar radiation, building load, and PV generation. These devices operation come to affect each other in the battery operation, where the building total load is introduced to the problem. Hence, if the battery management and grid constraints are removed from such a problem, the individual MPC would result in the same operation for the AC, EV, and water heater as the centralized MPC. The ability of this centralized controller to affect other devices load with respect to battery operation will give this controller more flexibility in control, and brings total awareness to the problem. Eq. (7) shows the general form of such a problem, combining four MPC problems of the EV, AC, water heater, and PV-battery into one centralized format.

$$\min \sum_{i=1}^{m} p_i \times P_G^i dt + \omega \varepsilon_i$$

Subject to: (7)

$$\begin{bmatrix} A_{AC} & 0 & 0 & 0 \\ 0 & A_{EV} & 0 & 0 \\ 0 & 0 & A_{WH} & 0 \\ a_1 & a_2 & a_3 & A_{Bat} \end{bmatrix} \begin{bmatrix} X_{AC} \\ X_{EV} \\ X_{WH} \\ X_{Bat} \end{bmatrix} \leq \begin{bmatrix} B_{AC} \\ B_{EV} \\ B_{WH} \\ B_{Bat} \end{bmatrix}$$

In this Problem A_{AC}, A_{EV}, A_{WH} and A_{Bat} are the constraint matrices explained in each device section, representing the model of each device and constraints in its operation with previously defined boundaries (B_{AC}, B_{EV}, B_{WH} and B_{Bat}). Objective of such a problem includes the total building operation cost and penalties for all slack variables. The objective function of such a problem can be constructed combining all previously defined objective functions (obj_i^{bat}, obj_i^{AC}, obj_i^{EV}, obj_i^{WH}). The following shows how the building total energy cost as the objective can perform the same as combination of previously define objectives:

$$\left\{\begin{matrix} P_G = P_L + P_R - P_I \\ P_L = P_{element} x_i^{WH} + P_C x_i^{EV} + P_{AC} x_i^{AC} + P_{rest} \end{matrix}\right\} \xRightarrow{MPC\ objective} p_i \times P_G^i dt + \omega \varepsilon_i \tag{8}$$

$$= p_i \times \left(P_L^i + P_R^i - P_I^i\right) dt + \omega \varepsilon_i$$

$$= p_i \times \left(P_{element} x_i^{WH} + P_C x_i^{EV} + P_{AC} x_i^{AC} + P_{rest} + P_R^i - P_I^i\right) dt + \omega_{EV} \varepsilon_{EV}^i + \omega_{AC} \varepsilon_{AC}^i$$
$$+ \omega_{wh} \varepsilon_{wh}^i + \omega_{Bat} \varepsilon_{Bat}^i$$
$$= \left(p_i P_{element} x_i^{WH} dt + \omega_{wh} \varepsilon_{wh}^i\right) + \left(p_i P_C x_i^{EV} dt + \omega_{EV} \varepsilon_{EV}^i\right)$$
$$+ \left(p_i P_{AC} x_i^{AC} dt + \omega_{AC} \varepsilon_{AC}^i\right) + p_i \times \left(P_{rest} + P_R^i - P_I^i\right) dt + \omega_{Bat} \varepsilon_{Bat}^i$$

P_{rest} is the rest of the load associated with other appliances consumption, which can be removed from objective as this load is not controllable in this MPC configuration and it is not a function of decision variables.

$$\Rightarrow p_i \times P_G^i dt + \omega \varepsilon_i = obj_i^{bat} + obj_i^{AC} + obj_i^{EV} + obj_i^{WH}$$

By removing the uncontrollable portion P_L and P_{rest}, the centralized formulation of the MPC control becomes:

$$min \sum_{i=1}^{m} p_i \times P_G^i \mathrm{dt} + \omega_{Bat} \varepsilon_{Bat}^i + \omega_{EV} \varepsilon_{EV}^i + \omega_{AC} \varepsilon_{AC}^i + \omega_{wh} \varepsilon_{wh}^i$$

Subject to:

$$\begin{aligned}
&P_G = P_L + P_R - P_I \\
&P_{PV} \eta_{con} = P_{BI} - P_{BO} + {P_I}/{\eta_I} - \eta_R P_R \\
&S_{Bat}^{i+1} = S_{Bat}^i + \frac{dt}{Q_{Bat}} \left(\eta_C P_{BI} - {1}/{\eta_D}\, P_{BO}\right) \\
&90 - \varepsilon_{Bat}^i < S_{Bat}^{i+1} < 20 + \varepsilon_{Bat}^i \\
&P_{Gmin} \le P_G \le P_{Gmax} \\
&0 \le {P_I}/{P_{Imax}} \le d_I \\
&0 \le {P_O}/{P_{Rmax}} \le 1 - d_I \\
&0 \le {P_{BO}}/{P_{Bmax}} \le d_B \\
&0 \le {P_{BI}}/{P_{Bmax}} \le 1 - d_B \\
&S_{LB_EV}^{i+1} - \varepsilon_{EV}^i < S_{EV}^{i+1} < S_{UB_EV}^{i+1} + \varepsilon_{EV}^i \\
&S_{EV}^{i+1} = S_{EV}^i + \frac{dt}{Q_{EV}} \left(\eta_c P_C x_{EV}^i - \eta_d P_d\right) \\
&T_{LB}^i - \varepsilon_{wh}^i < T_{wh}^{i+1} < T_{UB}^i + \varepsilon_{wh}^i
\end{aligned} \tag{9}$$

$$T_{wh}^{i+1} = T_{wh}^{i} + \frac{P_{element}}{C_{wh}} x_i \mathrm{dt} - \frac{\dot{m}C_w}{C_{wh}} \left(T_{wh}^{i} - T_{amb}\right)\mathrm{dt} - \frac{K_{wh}}{C_{wh}}\left(T_{wh}^{i} - T_{amb}\right)dt$$
$$LB_{AC} - k_{oc\_AC} \times (1 - OC_i) - \varepsilon_{AC}^{i} < T_{in}^{i+1} < UB_{AC} + k_{oc\_AC} \times (1 - OC_i) + \varepsilon_{AC}^{i}$$
$$T_{in}^{i+1} = T_{in}^{i} + \left(x_{AC}^{i}\right) \times \alpha_1 + \left(T_{out}^{i} - T_{in}^{i}\right) \times \alpha_2 + (Q_{solar}) \times \alpha_3 + \alpha_4$$
$$P_L = P_{element} x_{WH}^{i} + P_C x_{EV}^{i} + P_{AC} x_{AC}^{i}$$
$$x_{WH}^{i}, x_{EV}^{i}, x_{AC}^{i} \in \{0,1\}$$
$$d_I, d_B \in \{0,1\} \quad P_{BI},\ P_{BO}, P_I, \varepsilon_{Bat}^{i}, \varepsilon_{EV}^{i}, \varepsilon_{AC}^{i}, \varepsilon_{wh}^{i} \in \mathbb{R}_{\geq 0}$$

The MPC problem formulated in this configuration, has different prediction horizon for each device which is defined in each individual MPC problem. Optimization step is chosen as five minutes, corresponding to the lowest desired optimization resolution.

4 Results and Discussions

One year simulation is performed with three different pricing schemas to evaluate energy shifting capabilities and cost savings. The three pricing schemas are: TOU pricing from PG&E in California, day ahead hourly price from ComEd, and five minutes locational marginal price (LMP) from MISO. All prices are scaled to have an average value of 14 cents/kWh. Table 2 reports energy cost savings achieved in each device from traditional on/off to MPC controller. In Table 2 the EV, water heater, and AC savings are reported comparing with the standalone MPC controller and integrated MPC controller sing traditional rule based (on/off) controller as the baseline. The battery energy savings are related to comparing the centralized and standalone MPC with traditional controls of battery.

Table 2: Energy cost savings

Device:	**Overall**	**Battery**	**Electric Vehicle**	**Water Heater**	**AC**

Controller:	C-MPC	SA-MPC	C-MPC	SA-MPC	C-MPC	SA-MPC	C-MPC	SA-MPC	C-MPC	SA-MPC
Compared to:	RB	RB	RB-MPC*	RB-MPC*	RB	RB	RB	RB	RB	RB
Pricing										
RTP	42.5	42.6	26.5%	26.4%	31.0%	31.0%	28.1%	28.0%	22.3%	22.2%
TOU	26.4	21.8	19.3%	14.3%	14.8%	14.5%	17.4%	17.1%	14.7%	16.3%
Hourly	17.2	14.4	12.0%	9.1%	7.5%	7.5%	14.5%	14.0%	17.0%	18.6%

*RB-MPC: Traditional rule based (RB) battery management with standalone MPC for other devices
RB: On/off rule based controller
C-MPC: Centralized MPC controller
SA-MPC: Stand-alone MPC controller

These results show that this residential building could save more for all appliances when it is under a real time five minutes pricing, and save the least under an hourly pricing schema. This shows the effectiveness of TOU pricing in encouraging residential buildings to shift their consumption. RTP has the largest variance of 3 cent/kWh, TOU in the middle with variance of 0.5 cent/kWh, and DAP with 0.3 cent/kWh. However, frequency of changes and other factors might affect these savings as well.

4.1 Average building load on the grid

The following three graphs (Figure 9, Figure 10 and Figure 11), depicts one year average hourly energy consumption during a day in three pricing schemes (TOU, hourly, RTP). All rule based control refer to traditional methods of control in all devices, which has the same value in all graphs. Battery rule based refer to a test scenario where EV, water heater, and AC are controlled with standalone MPC and the battery is controlled using traditional rule based controller, which is the scenario of saving comparison reported in the previous table of savings for battery. Stand-alone MPC is when each device MPC is solved locally at each device and the battery uses control action prediction from other MPC controllers to design its control action. Finally, centralized MPC is the ideal situation where all devices and battery are controlled in one integrated MPC problem.

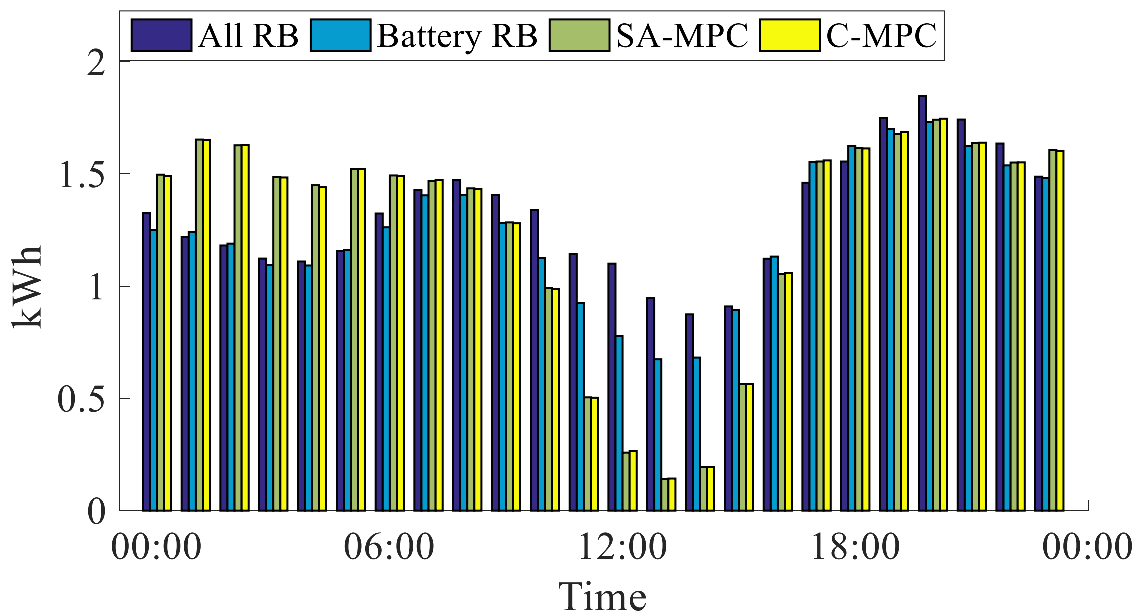

Figure 9: One year average Power flow from the grid in RTP

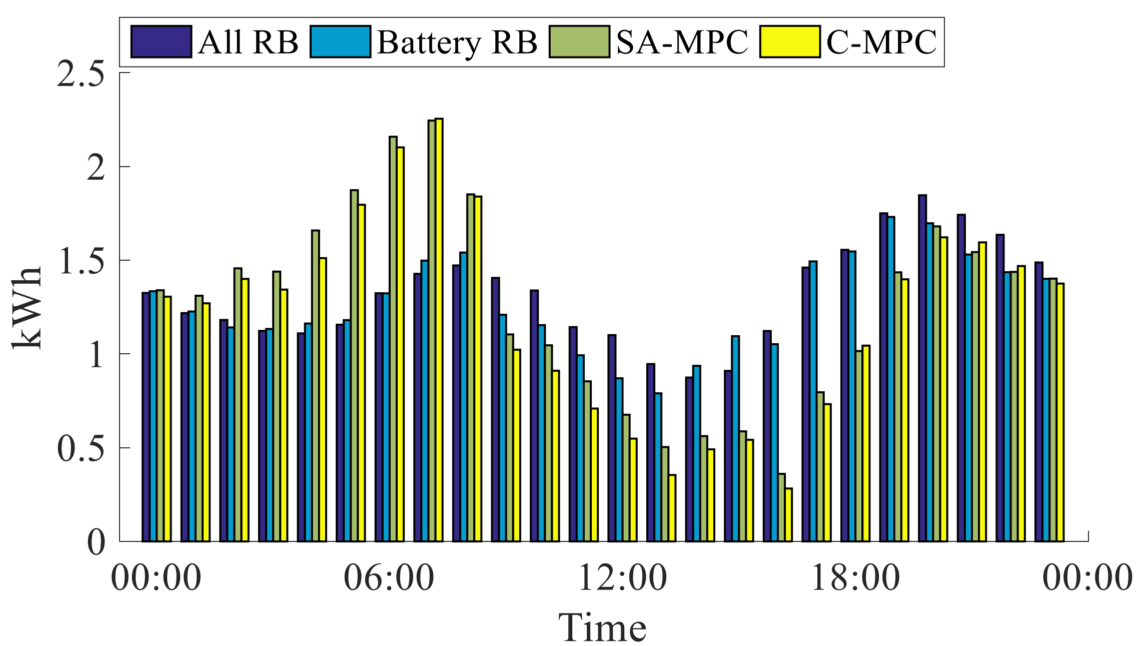

Figure 10: One year average Power flow from the grid in TOU pricing

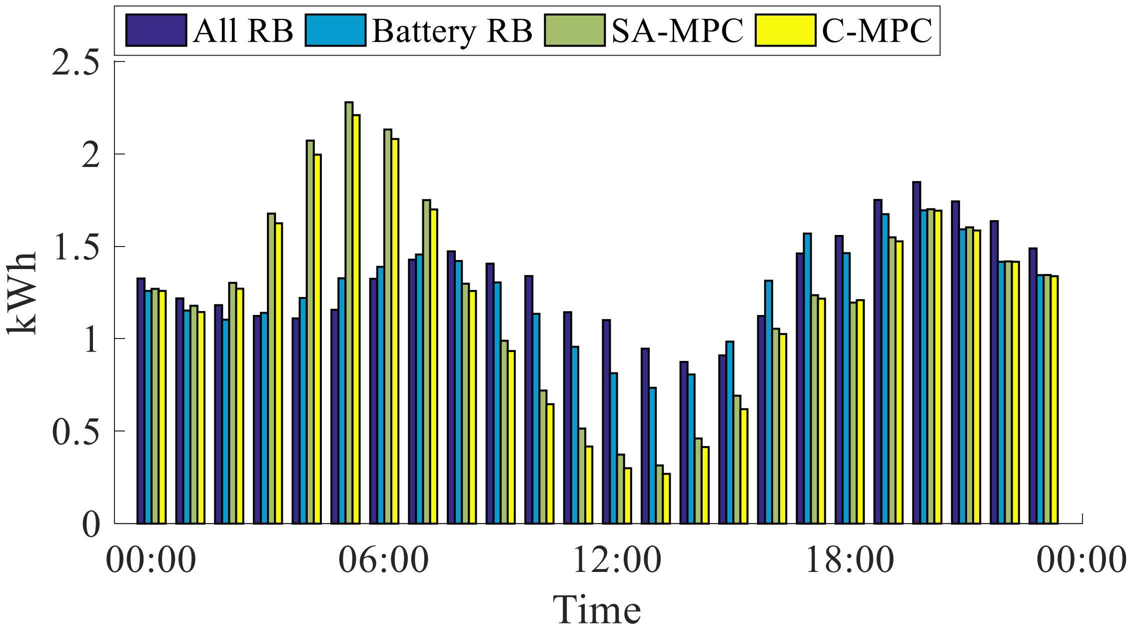

Figure 11: One year average Power flow from the grid in Hourly DAP

In all these figures (Figure 9, Figure 10 and Figure 11) the minimum required power from the grid happens at 1:00 PM corresponding to maximum PV generation. Maximum required power from the grid in a traditional operation happens at 8:00 PM corresponding to peak building consumption due to occupant behavior. However, under battery MPC control in both centralized and stand-alone schemes move the peak power flow to 5:00 AM in the hourly pricing and 7:00 AM in TOU pricing. Figure 9 shows that under RTP required power flow from the grid is more smoothed out with less peaks. This demonstrates the advantage of charging buildings under RTP compared to other pricing schemes from the grid perspective and peak shaving purposes. Figure 10 and Figure 11 show similar patterns for required power from grid.

4.2 Average battery load

Figure 12, Figure 13 and Figure 14 show the average battery power flow for one year simulation in each hour of the day for different pricing schemes. In all the pricing schemes the battery is being charged during the night and tempt to discharge during the day corresponding to lowest and highest average electricity price. In RTP (Figure 12) the battery discharging time falls in noon time to maximize grid feed-in corresponding to high average RTP in these hours. In TOU (Figure 13) discharging happen in peak price period between 2:00 PM and 9:00 PM, and in DAP (Figure 14) discharging happen between 8:00 AM and 7:00 PM. These discharging periods show how DAP pricing behave between RTP and TOU in grid favor. In other words, if we assume that the ideal building load on the grid behavior is happening in real time locational marginal pricing (RTP), then DAP have a closer behavior to the ideal behavior than TOU.

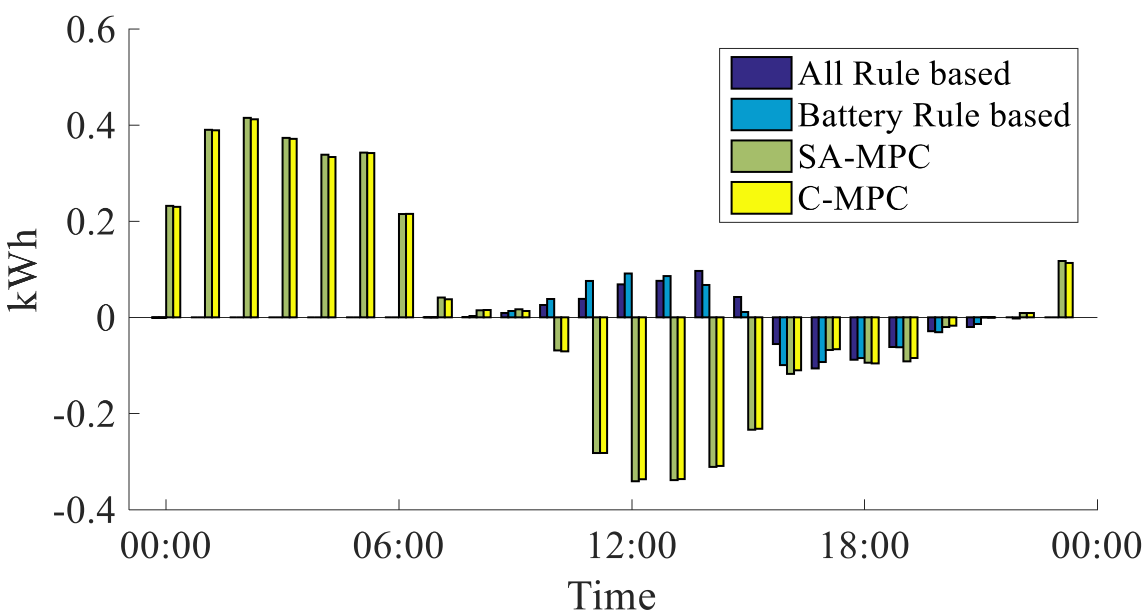

Figure 12: Average battery power flow in RTP

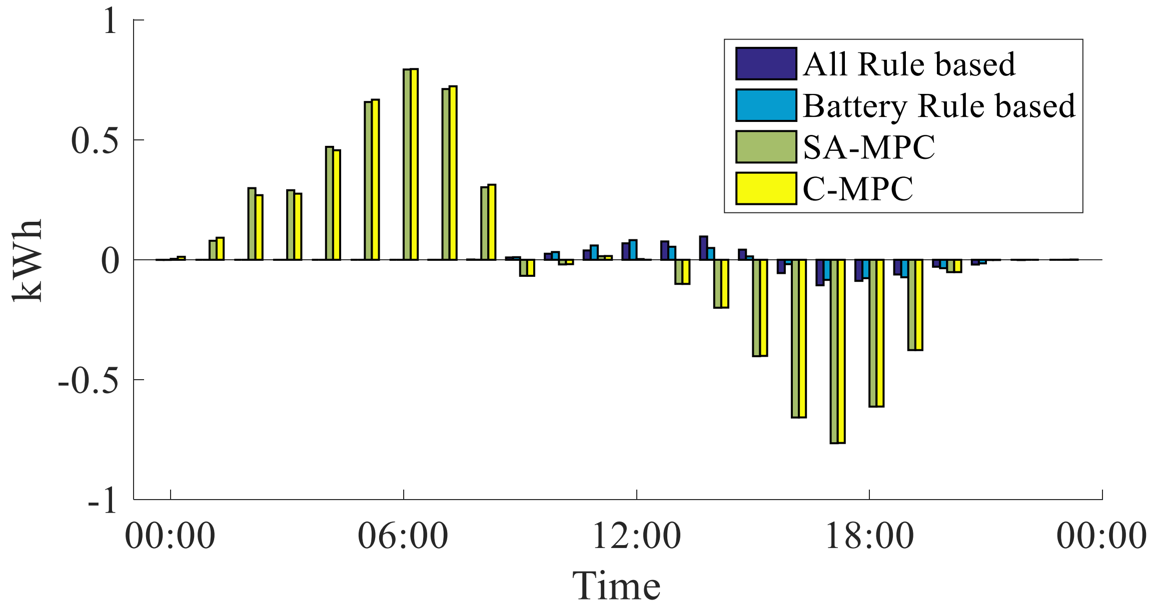

Figure 13: Average battery power flow in TOU

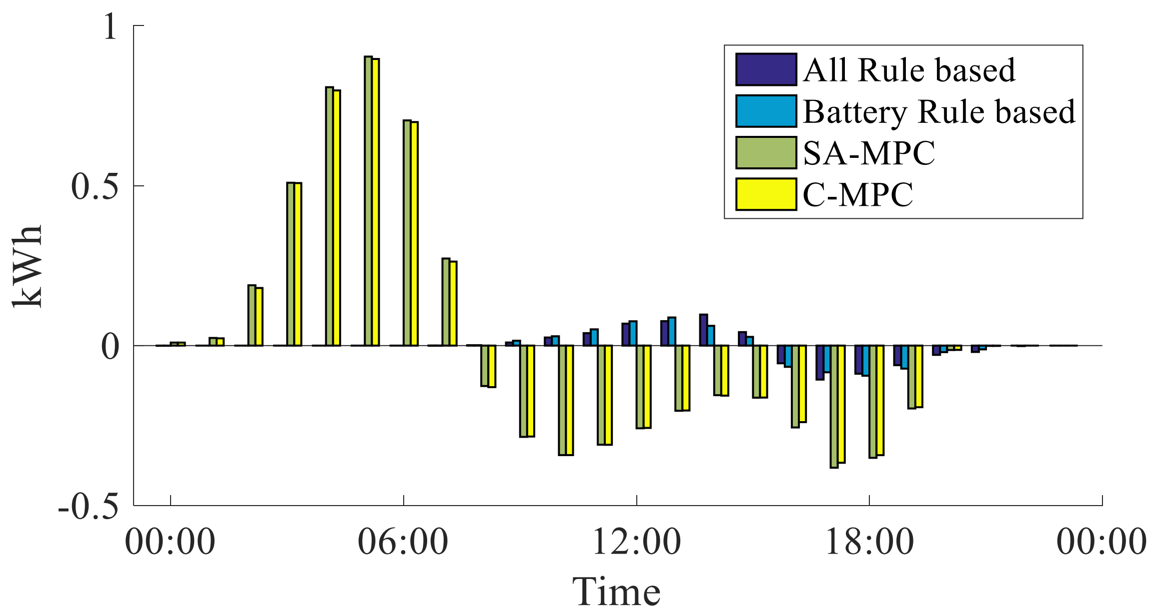

Figure 14: Average battery power flow in hourly DAP

4.3 Energy consumption Analysis

Figure 15, Figure 16, and Figure 17 show the average energy consumption of the EV, AC, and water heater for one year simulation in different pricings. The water heater consumption has a peak at 9:00 AM and 10:00 AM corresponding to occupant behavior on taking shower in studied residential building. This peak consumption has been smoothed out utilizing MPC controller for all pricing schemes. The EV has a peak energy consumption at 3:00 PM (Figure 16) corresponding to this residential building EV arrival time. In traditional charging control of EV there are barely any charging during the night. However, MPC shifts some of charging periods to nigh hours, when price of electricity is lower. It should be considered that, occupant behavior in using these devices, directly affect the amount of savings in each pricing scheme. For instance, if a device is usually being used around 9:00 AM is less capable in saving cost compared to a device which is usually being used around 9:00 PM. This is due to the fact that price of electricity is increasing for hours after 9:00 AM, so shifting consumption from 9:00 AM to later hours most likely will not save the cost. On the other hand, price of electricity tends to drop after 9:00 PM which brings opportunity for savings by few hours shifting.

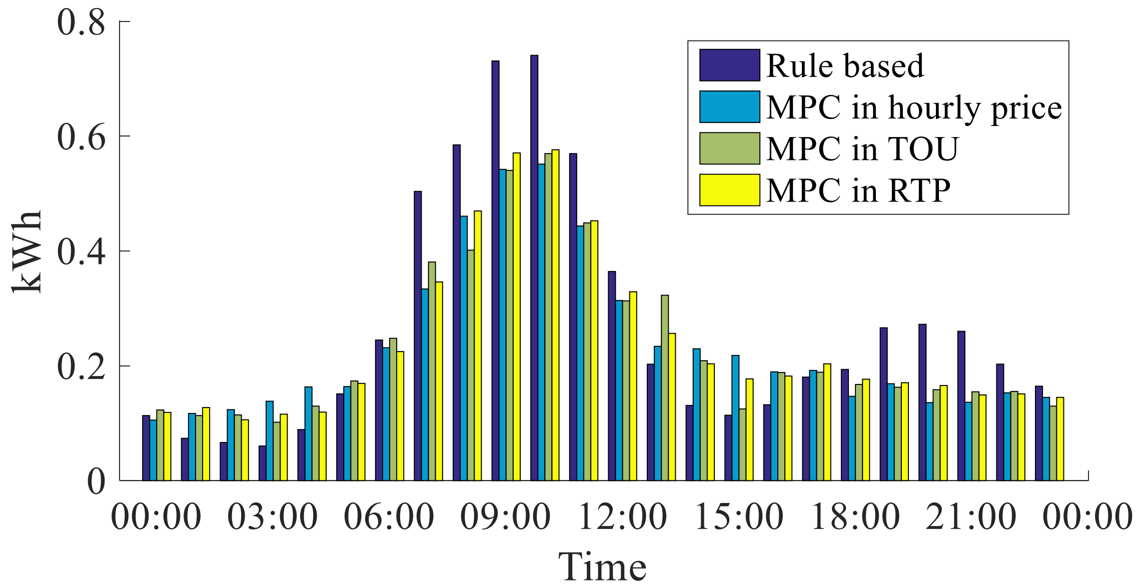

Figure 15: Water heater average electricity consumption in different pricings

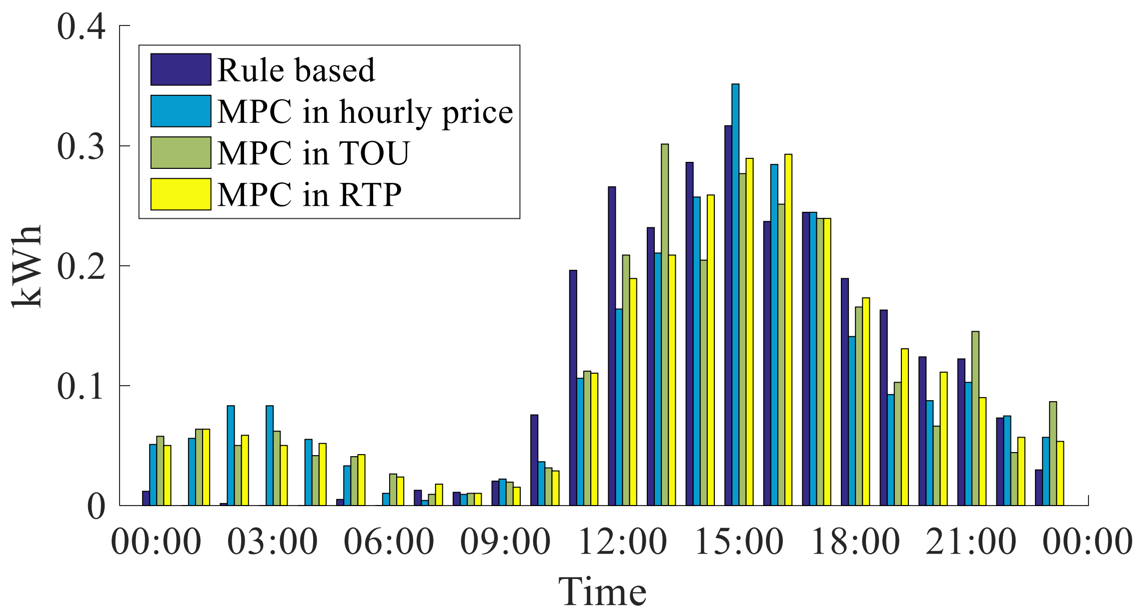

Figure 16: Electric Vehicle average electricity consumption in different pricings

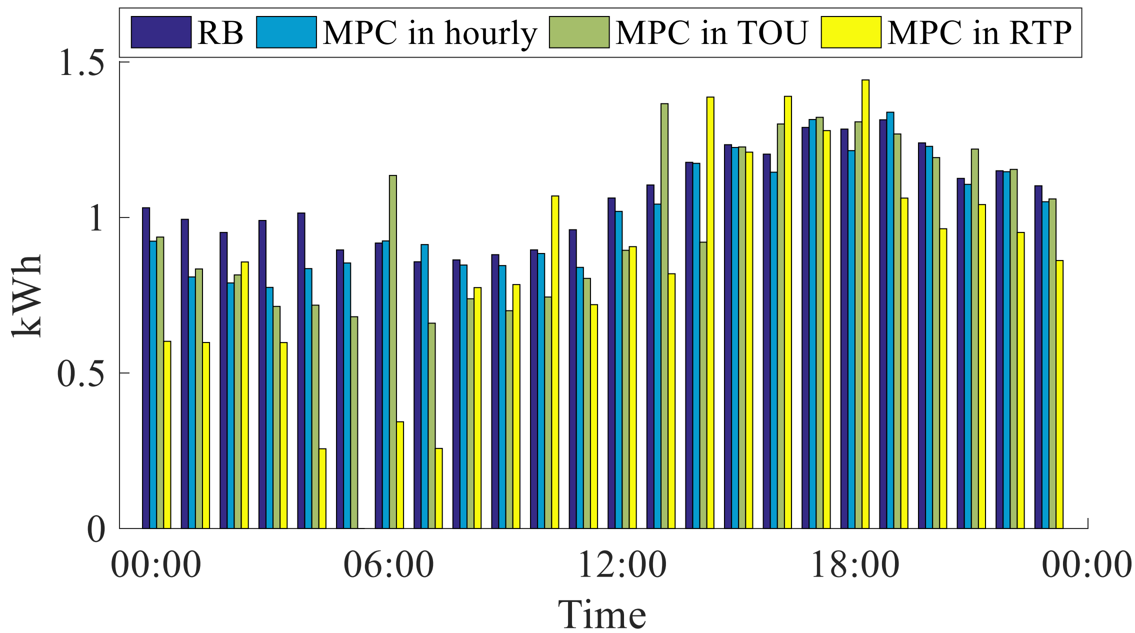

Figure 17: AC average electricity consumption in different pricings

4.4 Controlled variables under different pricing scenarios

Figure 18 and Figure 19 shows the battery SOC under different control strategies for RTP, and centralized MPC under three different pricing schemes. Battery SOC behave largely different in rule based controllers from MPC controllers as shown in Figure 19. Under TOU pricing, the battery is charged before the price rises and discharge when the price is high and correspond to PV generation and load. This charging and discharging periods are slightly different in hourly price as this pricing has more changes during a day, and much different in RTP. This behavior can result in slightly longer battery life in TOU pricing compared to other pricing methods, as the battery has less charging and discharging periods.

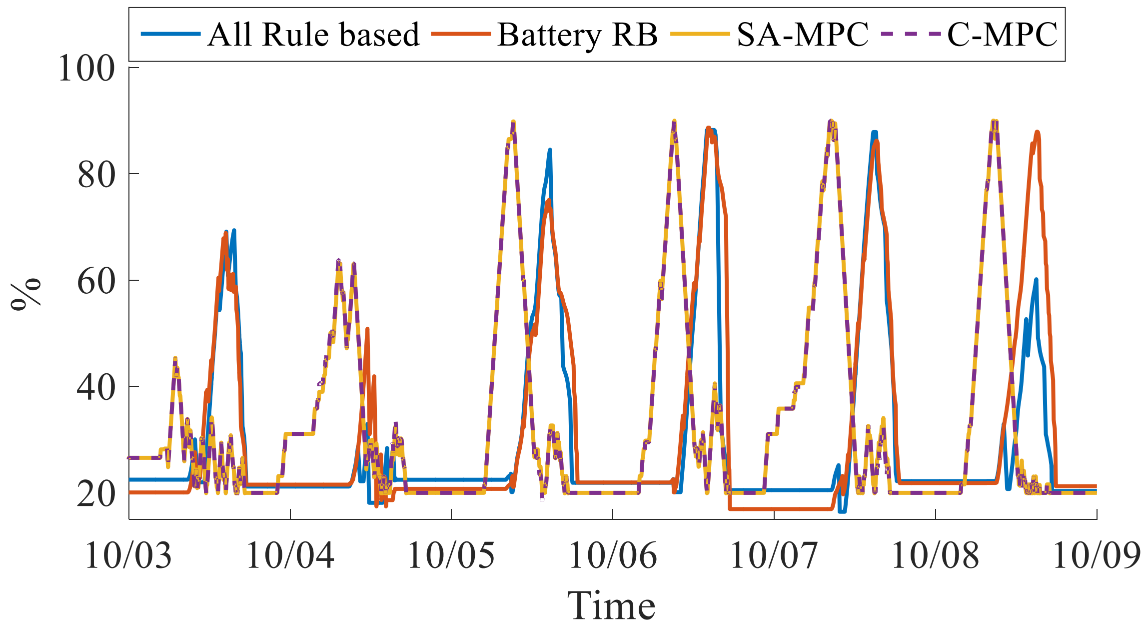

Figure 18: Battery SOC in different controllers in RTP

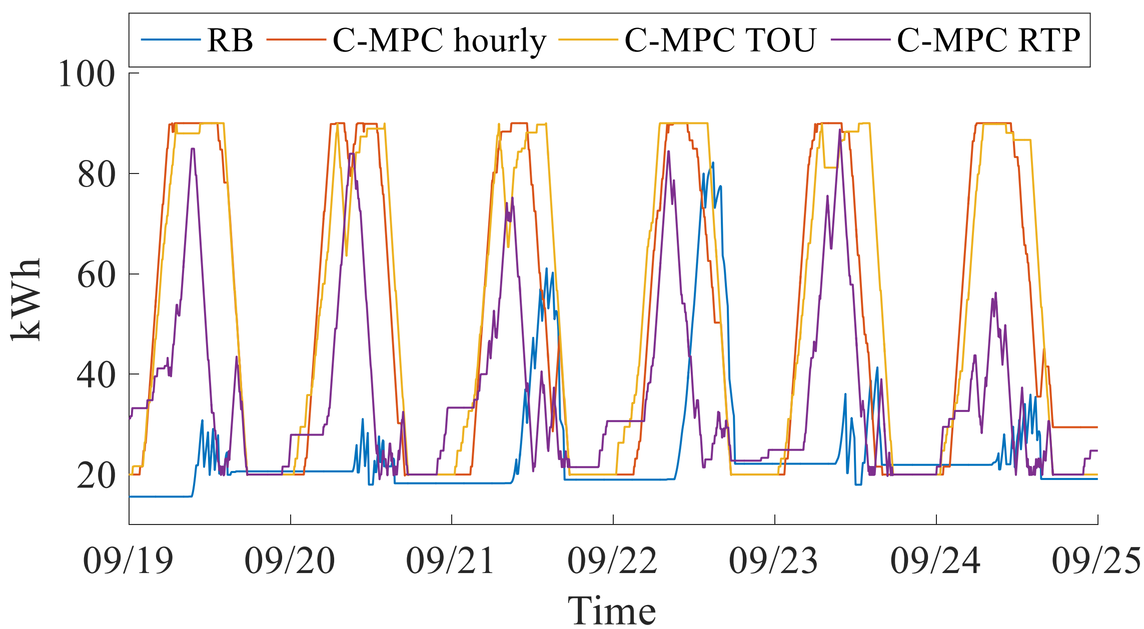

Figure 19: Battery SOC with C-MPC in different pricings

Figure 20, Figure 21, and Figure 22 show how each device behave in the behavior price driven MPC controllers. In Figure 20 EV SOC is maintained in the defined boundaries. The lower limit boundary is designed to charge the battery before the departure time. The SOC drops show EV usage estimated from the smart meter data and charging starts close to arrival time. In Figure 21 indoor temperature is maintained in the thermostat dead band, when the building is occupied and relaxed when the building is not occupied. In Figure 22 water temperature is maintained in the defined boundaries. Sharp temperature drops in this figure correspond to extreme hot water usage such as taking a shower.

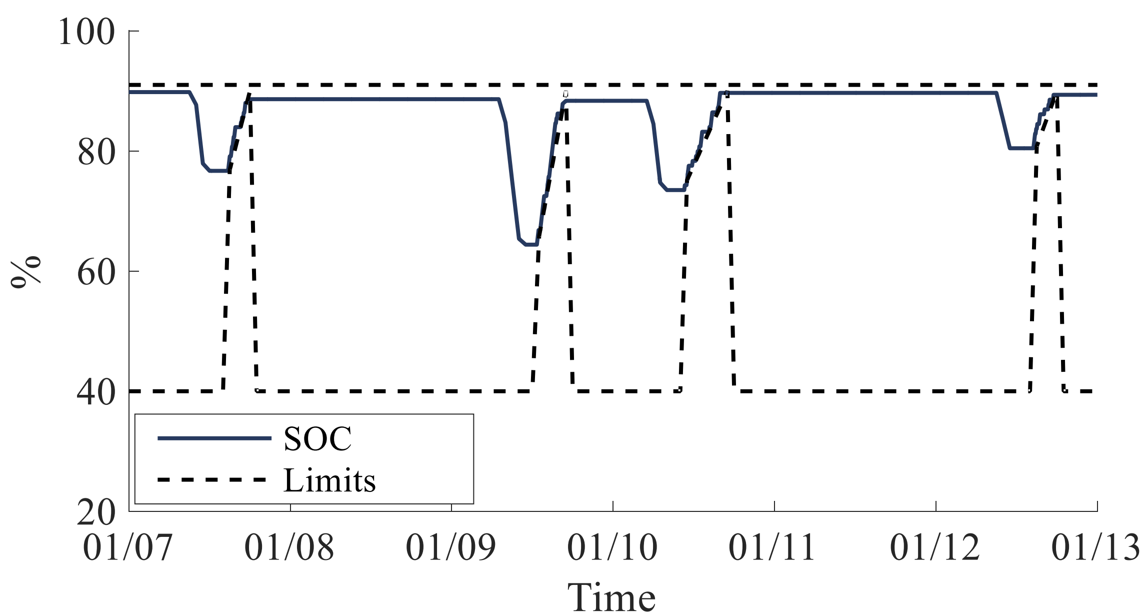

Figure 20: EV SOC MPC control

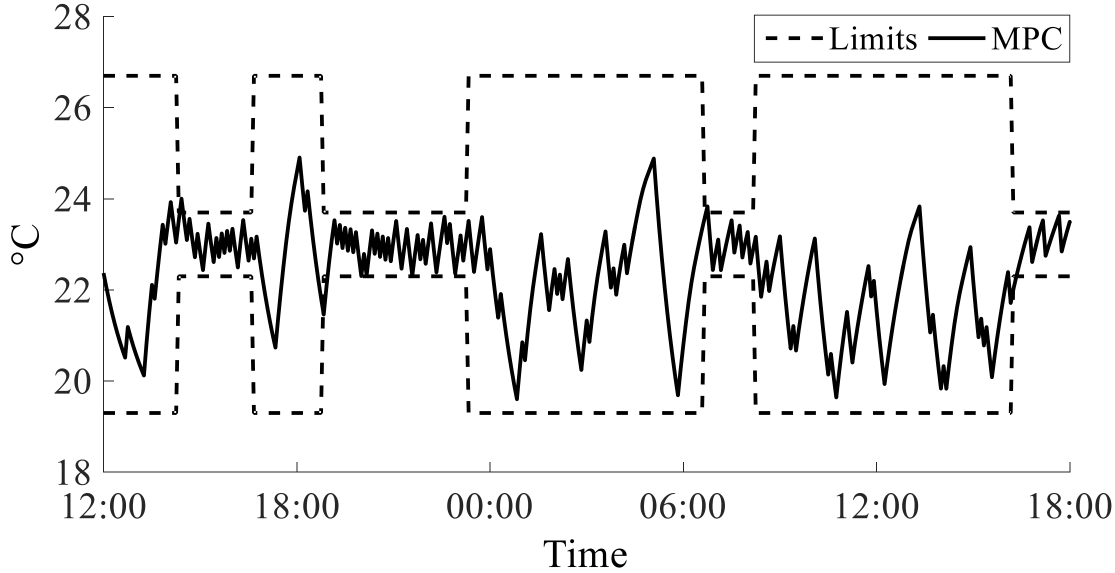

Figure 21: Indoor temperature with MPC control

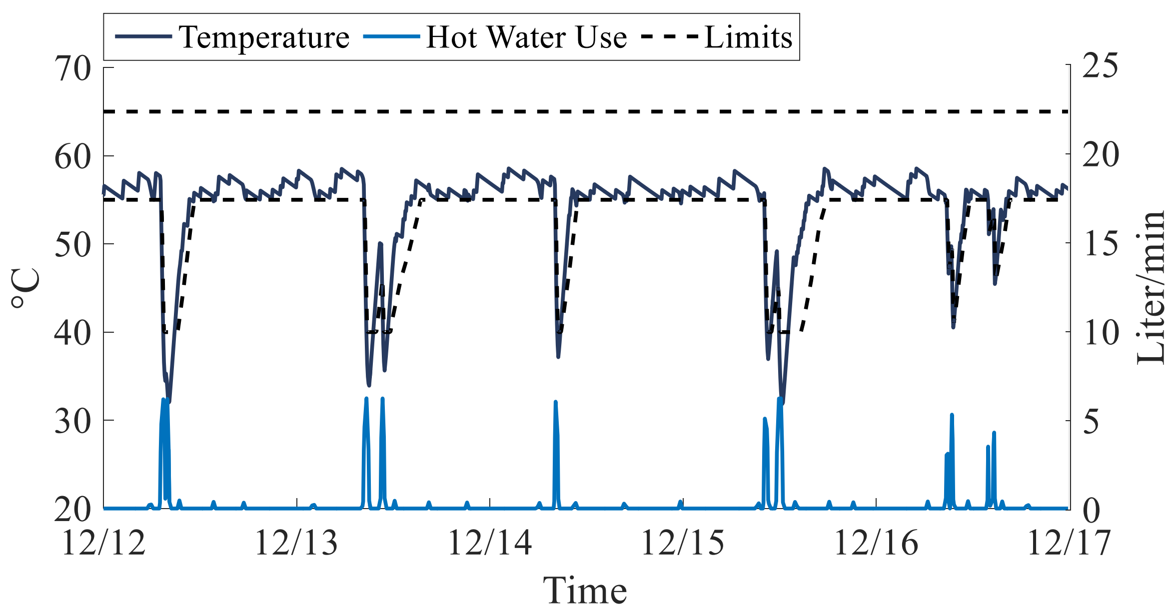

Figure 22: Water heater tank average temperature with MPC control

5 Conclusion

In this paper a behavior and price driven building energy management system for a residential building is introduced using MPC method. A centralized MPC configuration, and a stand-alone MPC configuration are compared with the traditional way of controls. An air conditioner, water heater, electric vehicle, and battery are controlled as the main consumers of electricity in a residential building. Occupant behavior is introduced into this control problem considering the occupancy presence in AC control, average hot water need by the occupants in water heater control, and driving patterns in EV charging control. Demand response capabilities of these controllers were tested in three different electricity rates, including: time of use, hourly and real time 5 minutes pricing. One year simulation results show that residential buildings can achieve cost savings up to 26% under TOU price, 42% under real time price, and 17% under hourly pricing, compared to traditional on/off controls. This savings shows the capabilities of TOU and RTP in affecting residential buildings operation.

The limitations of this study include: 1) occupancy presence data: it is a challenge to collect occupancy presence data in any residential building due to privacy issues. In this study, the occupancy presence data is given from another study [69]; and 2) lack of verification of observed behavior from smart meter data: we extract occupant behavior patterns from historical smart meter data without actual verification of that behavior due to limited access to the house;

The future study could focus on the impact of collective behavior of residential building load control on the smart grid. In other words, if all the buildings use the same control shifting strategy, it is possible that such control behavior could cause a frequency deviation problem for the grid operation.

Acknowledgement

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