

An approximate dynamic programming based home energy management
system and its impact on the distribution system

by

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Abstract

The residential sector consumes more than 20 percent of electricity in the United States. In order to shift peak load, a utility company provides time-of-use rates or even real-time pricing to its customers. Typically, peak electricity rates can be up to twice as much as the off-peak rates. Therefore, electricity costs can be different even when the customer is using the same amount of energy. A home energy management system (HEMS) can provide autonomous control of residential appliances to minimize the electricity cost while maintaining the customer's thermal comfort in the presence of uncertain weather and electricity consumption. In this thesis, a HEMS is developed to optimize forward-looking schedules for a residential home's heating, ventilation, air conditioning (HVAC), water heater (WH), electric vehicle (EV), and battery storage (ES). An approximate dynamic programming (ADP) approach is used to define, model, and solve the HEMS problem. Moreover, a model predictive control (MPC) based simulation framework is developed to study the impact of the HEMS on the distribution system and compare the ADP with another prevailing algorithm - mixed integer linear programming (MILP). Extensive simulation has been carried out and simulation results show that the proposed ADP-based HEMS can effectively schedule appliances to minimize the electricity cost and maintain customer thermal comfort. Furthermore, a coordinated two-stage real-time market mechanism in an unbalanced distribution system is proposed to fully utilize flexibility services provided by the HEMS for alleviating line congestion, voltage violation, and substation level power imbalance.

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Chapter 1

Introduction

With the development of smart grids the traditional power grid is undergoing tremendous changes, such that the growth in the deployment of distributed energy resources (DERs) and ever-increasing electricity demand give stress to our traditional distribution system³. Also, on the end-user side, residential electricity rates are changing from flat rates to time-of-use (TOU) rate plans. The U.S. Energy Policy Act of 2005 states that each electric power company should provide the customer with time-based rates⁴. In the United States, the residential sector consumes more than 20 of percent electricity, and most houses have deferrable or thermal loads such as dishwashers, air conditioners, water heaters, and electric vehicles. Therefore, the residential house has vast potential to contribute to or take advantage of this restructuring process. A home energy management system (HEMS) can automatically control the home appliances to balance user comfort and electricity costs, and can also serve as a demand response (DR) provider, which shifts the load and minimizes voltage violations and line congestions.

1.1 Background

Many researchers focus on HEMSs and develop various methods and solution algorithms for it⁵⁻¹³. Byun et al.⁵ proposed an intelligent cloud HEMS which assigns dynamic priority

to the appliance by considering the type of appliance and its current status. The schedule of each appliance is computed considering appliance priority and renewable energy capability. Jo et al.⁶ developed a smart heating and air conditioning scheduling method by using mixed integer non-linear programming (MINLP) considering customer convenience and characteristics of thermal appliances. Shafie-Khah and Siano⁷ considered the response fatigue phenomenon in the HEMS models to mitigate consumers from getting tired to make decisions based on different tariffs and electricity usage. Zhao et al.⁸ proposed a power scheduling method by combining real-time pricing with the inking block rate, which can reduce both electricity cost and peak-to-average load ratio. Pedrasa et al.⁹ developed a method which enables users to assign a value to desired energy services, and schedule distributed energy resources by using particle swarm optimization to maximize net benefits. Deng et al.¹⁰ proposed a method to solve the stochastic load scheduling problem in HEMS, which uses dual decomposition and stochastic gradient. Chang et al.¹¹ introduced a coordinated HEMS, where distributed HEMSs among neighbor can collaborate with each other to balance real-time power. Shakeri et al.¹² proposed a controller which can select electricity sources and give decisions to appliances in real-time based on appliance request and electricity price. Also, Ahmed et al.¹³ proposed a real-time system for HEMS, in which real-time schedule controllers turn on and off each appliance based on the demand response.

1.2 Related Work

Dynamic programming (DP) is a common algorithm when implementing HEMSs. Liu et al.¹⁴ proposed a DP algorithm to control home appliances with multiple discrete power levels to reduce electricity costs. DP faces three curses of dimensionality where the size of state space, outcome space, and action space grow dramatically when the dimension grows. This is challenging because it has to go through every state to get an optimal policy¹⁵. Livengood and Larson¹⁶ proposed a stochastic DP algorithm which generalizes and limits the state space of HEMS in order to overcome the state explosion. Liang et al.¹⁷ proposed an optimal control for demand-side management of smart appliances with time-varying prices. The problem

is formulated as a dynamic programming model, capturing the stochasticity in demand arrivals, where a decentralized heuristic approach and approximation-based Q-learning method are proposed to overcome the curse of dimensionality in the problem. Approximate dynamic programming (ADP) becomes the upgraded version of DP. The idea of ADP is to estimate the value function by using various approaches to avoid examination of every state. The method perfectly solves the state explosion and massive optimal decision making under uncertainty^{15;18}.

A number of past HEMS efforts have explored using ADP for PV-battery management^{19–22}. Keerthisinghe et al.¹⁹ uses ADP with temporal difference learning to implement a computationally efficient HEMS that optimizes PV-battery system scheduling for minimal cost and user discomfort. Wei et al.²⁰ proposes a novel distributed iterative ADP to solve the multi-battery optimal coordination control problems. Huang and Liu²¹ develop a self-learning scheme based on ADP to optimize residential energy systems. Squartini et al.²² compare different methods for home energy resource scheduling and analyzes their performance dependency on the battery model employed, focusing on battery capacity and charge/discharge rates. A few other studies have used ADP to control the energy use of building cooling systems to minimize energy consumption while preserving occupant comfort^{23;24}.

1.3 Contributions

In this thesis, a HEMS algorithm is proposed to minimize household electricity cost while maintaining user comfort when faced with uncertain weather and user demand. The major contributions are summarized in the following subsections.

1.3.1 DP and ADP HEMS Modeling and Simulation

The HEMS problem is modeled by using dynamic programming techniques and use traditional DP and sample backward induction (SBI) ADP to solve the problem. In the HEMS problem, we consider three appliances including a home’s heating, ventilation, and air condi-

tioning (HVAC), water heater (WH), and electric vehicle (EV) and optimize their forward-looking schedules while considering the uncertainty in outside temperature, hot water usage and non-controllable loads (NCL). We model the problem in terms of a DP problem with the state, decision, and uncertainty variables. In each hour, the HEMS makes decisions including the setpoint for the HVAC system and water heater and the charge or discharge schedule for an electric vehicle (EV). In this work, we compare the DP and ADP performance and examine the HEMS decision results. ADP offers a promising approach to solve the HEMS scheduling problem under uncertainty effectively. Details of this work are presented in Chapter 2 and the following publication:

M. N. Faqiry, L. Wang, H. Wu, D. Krishnamurthy, and B. Palmintier. ADP-based Home Energy Management System: A Case Study using DYNAMO. In *2018 IEEE Power Energy Society General Meeting (PESGM)*, pages 1–5, August 2018. doi: 10.1109/PESGM.2018.8585796¹.

1.3.2 ADP versus MILP Comparison

Mixed linear integer programming (MILP) is another traditional approach to solve the HEMS problem. In order to compare MILP with ADP, we adopt DP formula which contains Markov state transition functions, an objective function and constraints to form our mathematical model. The same mathematical equations are used for MILP. In addition, a model predictive control (MPC) simulation framework is developed to examine the performance of two methods. The result shows MILP and ADP have similar decisions and objective values, and both can effectively solve the HEMS problem. The ADP model has less accurate control of the room and water temperature. However, it is straightforward to introduce non-linearity in the objective functions and constraints in ADP model, whereas that is not the case for MILP. The stochastic impact is quite small in the HEMS problem in each method because of the low weight associated with stochastic variable terms. Also, the MPC framework on its own has the capability to deal with the stochastic errors by updating the stochastic variables

repeatedly over the simulation horizon. Details of this work are presented in Chapter 3.

1.3.3 HEMS-Enabled Transactive Flexibility in Real-Time Operation of Three-Phase Unbalanced Distribution Systems

ADP based HEMS not only has the ability to reduce the users electricity cost while maintaining the users comfort, but can also contribute positively to the distribution system. Chapter 4 describes a two-stage mechanism and optimization problem for each stage to minimize the line congestion, voltage violation and power imbalance of an unbalanced distribution system while maintaining user comfort and reducing electricity cost under uncertain future demand and weather conditions. We model and simulate the whole structure from the distribution system operator (DSO) level to the individual home level on a modified IEEE 69-node distribution system. Simulation shows the HEMS can adequately provide the flexibility to the DSO based on the DSO price signal while meeting the user demand. The DSO can also solve distribution system issues by using given flexibility from the HEMS. Therefore, we believe that the HEMS can be the major demand response (DR) provider in the future smart grid system. Details of this work are presented in Chapter 4 and the following publication:

M. N. Faqiry, L. Wang, and H. Wu. HEMS-Enabled Transactive Flexibility in Real-Time Operation of Three-Phase Unbalanced Distribution Systems. *Journal of Modern Power Systems and Clean Energy*, In press².

1.4 Organization

Chapter 2 defines details of the DP formulation of the HEMS problem and the ADP SBI algorithm, then compare DP versus ADP performance in the context of computation time and solution quality. Furthermore, the ADP method is used to solve the HEMS scheduling problem. Chapter 3 compares the ADP with another promising algorithm MILP in HEMS. Same mathematical formula is adopted for both algorithms to evaluate them and make a

fair comparison. A MPC framework is developed and used to simulate both algorithms. Chapter 4 introduces an approach to integrate HEMS with smart grid in order to minimize line congestion, voltage violation, and power imbalance on the distribution system while maintaining comfort and minimizing electricity cost for users. Results show the HEMS can not only contribute the user side such as saving electricity cost but also benefit the distribution system level in a smart grid. Chapter 5 summarizes this thesis and presents future work.

Chapter 2

ADP-based Home Energy Management System

In this chapter, development of an ADP based home energy management system to minimize electricity cost while maintaining user comfort when encountered with uncertain weather and user demand is presented. HEMS is used to schedule multiple appliances and determine set-points for HVAC unit, heating setpoints for the water heater, and charge/discharge schedules for the electric vehicle.

Table 2.1: Notation.

$\mathcal{D}$	Discomfort function
$\mathcal{C}$	Cost function
$\mathcal{F}_s$	Sample function
$\bar{V}_t$	Approximate value function
s_t^{HVAC}	State of HVAC at time t (°F)
s_t^{WH}	State of WH at time t (°F)
s_t^{EV}	State of EV at time t (% State of Charge (SOC))
s_t	State set tuple $\{s_t^{HVAC}, s_t^{WH}, s_t^{EV}\}$

s_t^*	Sampled state set tuple at time t
$\mathbf{S}_t$	All possible state sets at time t
$\mathbf{S}_t^*$	Sampled all possible state sets at time t
x_t^{HVAC}	Decision for HVAC at time t (°F)
x_t^{WH}	Decision for WH at time t (°F)
x_t^{EV}	Decision of EV at time t (% SOC)
x_t	Decision set tuple $\{x_t^{\text{HVAC}}, x_t^{\text{WH}}, x_t^{\text{EV}}\}$
x_t^*	Sampled decision set tuple at time t
$\mathbf{X}_t$	All possible decision sets at time t
$\mathbf{X}_t^*$	Sampled all possible decision sets at time t
$\tilde{u}_t^{\text{OUT}}$	Stochastic outside temperature at time t (°F)
$\tilde{u}_t^{\text{WH}}$	Stochastic hot water demand of household at time t (gal./hr)
$\tilde{u}_t^{\text{NCL}}$	Stochastic NCL demand of household (kW)
$\tilde{u}_t$	Stochastic variables set tuple at time t $\{\tilde{u}_t^{\text{OUT}}, \tilde{u}_t^{\text{WH}}, \tilde{u}_t^{\text{NCL}}\}$
$\tilde{u}_t^*$	Sampled stochastic variables set tuple at time t
$\tilde{\mathbf{U}}_t$	All possible stochastic variables sets at time t
$\tilde{\mathbf{U}}_t^*$	Sampled all possible stochastic variables sets at time t
$\alpha_t^{\mathcal{D}}$	Weighted sum coefficient for discomfort
$\alpha_t^{\mathcal{C}}$	Weighted sum coefficient for cost
s_t^{HVACd}	Desired state of HVAC at time t (°F)
s_t^{WHd}	Desired state of WH at time t (°F)
s_t^{EVd}	Desired state of EV at departure time t_d (% State of Charge (SOC))
β_t^{HVAC}	HVAC discomfort coefficient
β_t^{WH}	WH discomfort coefficient
β_{td}^{EV}	EV discomfort coefficient at departure time t_d
c_t	Price of electricity at time t (\$/kWhr)

p_t^G	Power purchased from the grid (kW)
γ^{RM}	Room insulation thermal efficiency coefficient
γ^{OUT}	Outside temperature thermal influence coefficient
γ^{HVAC}	HVAC unit conversion coefficient ($^{\circ}\text{F}$)
$\underline{s}_t^{\text{HVAC}}$	Min. temperature setting for HVAC at time t ($^{\circ}\text{F}$)
$\bar{s}_t^{\text{HVAC}}$	Max. temperature setting for HVAC at time t ($^{\circ}\text{F}$)
$\underline{x}_t^{\text{HVAC}}$	Min. HVAC decision limit at time t ($^{\circ}\text{F}$)
$\bar{x}_t^{\text{HVAC}}$	Max. HVAC decision limit at time t ($^{\circ}\text{F}$)
$\gamma^{\text{WH,C}}$	Thermal natural cooling coefficient of WH
γ^{USG}	Hot water usage unit conversion coefficient ($^{\circ}\text{F}/\text{gal}$)
γ^{WH}	WH unit conversion coefficient ($\text{kW}/^{\circ}\text{F}$)
$\underline{s}_t^{\text{WH}}$	Min. temperature setting for WH at time t ($^{\circ}\text{F}$)
$\bar{s}_t^{\text{WH}}$	Max. temperature setting for WH at time t ($^{\circ}\text{F}$)
$\underline{x}_t^{\text{WH}}$	Min. WH decision limit at time t ($^{\circ}\text{F}$)
$\bar{x}_t^{\text{WH}}$	Max. WH decision limit at time t ($^{\circ}\text{F}$)
γ^{EV}	EV unit conversion coefficient ($\text{kW}/\%\text{SOC}$)
$\gamma^{\text{EV,L}}$	EV energy loss (self-discharge) coefficient
$\gamma^{\text{EV,C}}$	EV charging efficiency coefficient
$\gamma^{\text{EV,NCL}}$	EV SOC unit conversion coefficient ($\%\text{SOC}/\text{kWh}$)
$\underline{s}_t^{\text{EV}}$	EV minimum state of charge($\%\text{SOC}$)
$\bar{s}_t^{\text{EV}}$	EV maximum state of charge($\%\text{SOC}$)
$\underline{x}_t^{\text{EV}}$	EV minimum decision limit ($\%\text{SOC}$)
$\bar{x}_t^{\text{EV}}$	EV maximum decision limit ($\%\text{SOC}$)
t_a/t_d	Arrival/departure time of EV
Δt	Time interval resolution
T	Look-ahead horizon

$V_t(s_t)$	Optimal objective value of current state set at time t
$V_t^*(s_t^*)$	Optimal objective value of current sampled state set at time t

2.1 Problem Formulation

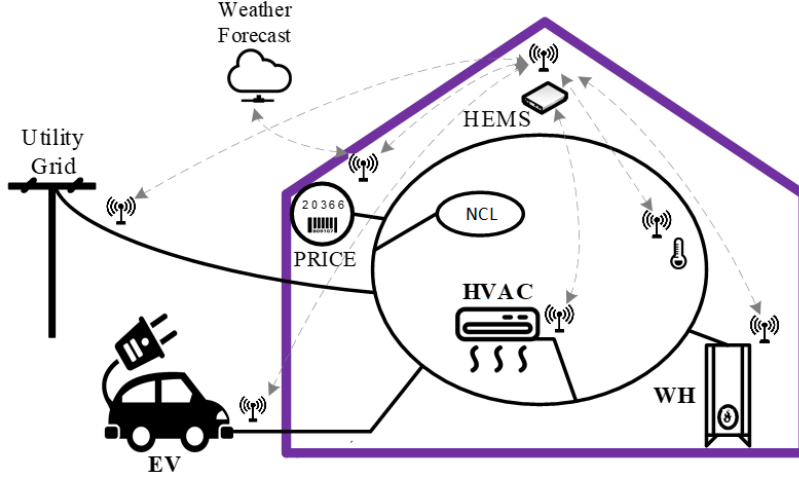


Figure 2.1: *Schematic diagram of HEMS¹.*

Consider the HEMS schematic in Fig. 2.1. The goal is to minimize the weighted sum of the household's discomfort and cost by determining the HVAC setpoint, WH setpoint, and EV charge/discharge schedule while looking forward multiple time steps to also endogenously capture future uncertainty. This problem can be modeled in terms of a DP with states, decisions, and stochastic variables.

At every time step, the HVAC, WH, and EV states are respectively considered as the room temperature, water temperature, and EV battery state-of-charge (SOC). The decision set captures whether or not to run the HVAC system and at what fan speed, whether or not to heat water in the WH, and how much energy to withdraw from the EV battery. Uncertainty is also considered in outside temperature, hot water demand, and other non-controllable loads of the household. Additionally, the following timing assumptions are made:

- 1) The appliance is in state s_t when HEMS makes a decision x_t at the beginning of the time step.

- 2) The decision is applied immediately and impacts the remainder of the time step.
- 3) The stochastic variable associated with the appliance is realized after the decision is applied and lasts for the remainder of the time step.

Mathematically, the state, decision, and uncertainty set tuple $\{s_t, x_t, \tilde{u}_t\}$ covers HVAC, WH and EV for all time periods, i.e. $\forall t \in \{0, \dots, T\}$

$$\{s_t, x_t, \tilde{u}_t\} = \{(s_t^{\text{HVAC}}, s_t^{\text{WH}}, s_t^{\text{EV}}), (x_t^{\text{HVAC}}, x_t^{\text{WH}}, x_t^{\text{EV}}), (\tilde{u}_t^{\text{HVAC}}, \tilde{u}_t^{\text{WH}}, \tilde{u}_t^{\text{EV}})\}$$

The HEMS objective can be achieved in terms of the following optimization problem using a form of Bellmans equation. [18;25](#)

$$\min_{x_t} \mathbb{E} \left\{ \sum_{t=0}^T \alpha_t^{\mathcal{D}} \cdot \mathcal{D}_t(s_t) + \alpha_t^{\mathcal{C}} \cdot \mathcal{C}_t(s_t, x_t) \right\} \quad (2.1)$$

The objective function in [2.1](#) shows the expected weighted sum of discomfort $\mathcal{D}_t$ and cost $\mathcal{C}_t$ over the look-ahead horizon. The discomfort and cost functions are given below.

$$\begin{aligned} \mathcal{D}_t(s_t) = & \beta_t^{\text{HVAC}} * \text{abs}(s_t^{\text{HVACd}} - s_t^{\text{HVAC}}) + \beta_t^{\text{WH}} * \text{abs}(s_t^{\text{WHd}} - s_t^{\text{WH}}) \\ & + \beta_{t_d}^{\text{EV}} * \max((s_{t_d}^{\text{EVd}} - s_{t_d}^{\text{EV}}), 0) \end{aligned} \quad (2.2)$$

$$\mathcal{C}_t(s_t, x_t) = c_t p_t^G \Delta t \quad (2.3)$$

In Equation [2.2](#), the discomfort due to each appliance is modeled as the absolute value of the deviation from their respective desired values. Each discomfort term is weighted differently to accommodate the users preferences for each appliance. For the EV, only the departure time dissatisfaction is included which means that only when $t = t_d$, $\beta_{t_d}^{\text{EV}}$ has value and is zero at all other times. It is assumed the user only cares about the departure time SOC and does not experience any discomfort due to low SOC when the EV is at home. The cost function in [2.3](#) is computed as the total electricity cost of the power imported from the grid over the look-ahead horizon. Here, every household is assumed to be a price taker. The power imported from the grid is computed as the sum of decisions, i.e. $P_t^G = \gamma^{\text{HVAC}} * x_t^{\text{HVAC}} + \gamma^{\text{WH}} * x_t^{\text{WH}} + \gamma^{\text{EV}} * x_t^{\text{EV}}$. The constraints for [2.1](#) are given as the state transition functions and other limiting constraints

explained below.

HVAC:

$$s_t^{\text{HVAC}} = \begin{cases} \gamma^{\text{RM}} s_{t-1}^{\text{HVAC}} - x_t^{\text{HVAC}} + \gamma^{\text{OUT}} \tilde{u}_t^{\text{OUT}}, & \text{if cooling} \\ \gamma^{\text{RM}} s_{t-1}^{\text{HVAC}} + x_t^{\text{HVAC}} + \gamma^{\text{OUT}} \tilde{u}_t^{\text{OUT}}, & \text{if heating} \end{cases} \quad (2.4)$$

$$\underline{s}_t^{\text{HVAC}} \leq s_t^{\text{HVAC}} \leq \bar{s}_t^{\text{HVAC}} \quad (2.5)$$

$$\underline{x}_t^{\text{HVAC}} \leq x_t^{\text{HVAC}} \leq \bar{x}_t^{\text{HVAC}} \quad (2.6)$$

$$\underline{x}_t^{\text{HVAC}} \leq x_t^{\text{HVAC}} \leq \bar{x}_t^{\text{HVAC}} \quad (2.7)$$

Equation 2.4 shows the state transition of the room temperature for both cooling and heating modes that are pre-determined. The current room temperature depends on the room temperature of the previous time and current outside temperature. Note that in this control implementation, the HVAC efficiency is embedded in the cost function and building thermal properties as captured by building and outside air temperature driven factors γ^{RM} and γ^{OUT} , respectively. Also, the control decision, x_t^{HVAC} , is computed in units of thermal energy added or removed. This control can later be adapted to corresponding thermostat settings. Equations 2.5, 2.6, 2.7 indicate that, for both cooling and heating cases, the states and the decisions have to lie within the specified bounds.

WH:

$$s_t^{\text{WH}} = \gamma^{\text{WH,C}} s_{t-1}^{\text{WH}} + x_t^{\text{WH}} - \gamma^{\text{USG}} \tilde{u}_t^{\text{WH}} \Delta t \quad (2.8)$$

$$\underline{s}_t^{\text{WH}} \leq s_t^{\text{WH}} \leq \bar{s}_t^{\text{WH}} \quad (2.9)$$

$$\underline{x}_t^{\text{WH}} \leq x_t^{\text{WH}} \leq \bar{x}_t^{\text{WH}} \quad (2.10)$$

Similarly, Equations 2.8, 2.9, 2.10 show the state transition of water temperature and the state and decision limit constraints of the water heater.

EV:

$$s_t^{\text{EV}} = \begin{cases} \gamma^{\text{EV,L}} s_{t-1}^{\text{EV}} + \gamma^{\text{EV,C}} x_t^{\text{EV}} - \gamma^{\text{EV,NCL}} \tilde{u}_t^{\text{NCL}} \Delta t, & t_a \leq t \leq t_d \\ \text{Constant}, & \text{Otherwise} \end{cases} \quad (2.11)$$

$$\underline{s}_t^{\text{EV}} \leq s_t^{\text{EV}} \leq \bar{s}_t^{\text{EV}} \quad (2.12)$$

$$-\underline{x}_t^{\text{EV}} \leq x_t^{\text{EV}} \leq \bar{x}_t^{\text{EV}} \quad (2.13)$$

When the EV is at home, Equation 2.11 captures its SOC lost by self-discharge over time²⁶, charging/discharging decision of HEMS, and the amount of random NCL consumed. It is assumed that when the EV is at home, it feeds the household stochastic NCL. However, when the EV is not at home, the grid directly feeds the stochastic NCL, and HEMS only optimizes decisions for HVAC and WH. Equations 2.12 and 2.13 indicate that the EV state and decision must lie within the specified bounds.

2.2 DP and ADP algorithm

As an example, Fig. 2.2 diagrams the HVAC point setting portion of the problem as a decision tree. Here, squares, circles, and triangles represent decision, uncertainty, and terminal nodes, respectively. The decisions are STAY (no action), COOL, or H.COOL (high cool). The outside temperature is modeled from historical data, but its forecast is estimated as a generalized random walk that may go up or down a few degrees or remain unchanged. The optimal DP solution can be found using backward induction²⁷ in Algorithm 1.

$\mathbf{S}_t$ represents the state set including all possible states at time t , and $\mathbf{X}_t$ represents the

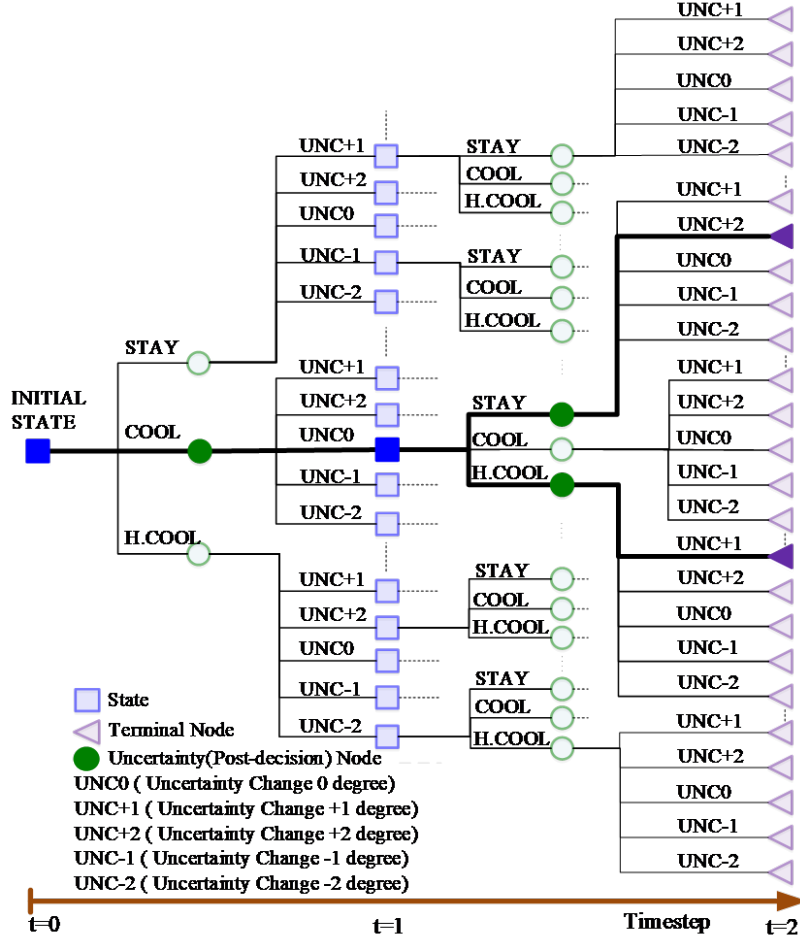


Figure 2.2: Decision tree for HVAC with highlighted route that minimizes expected weighted sum of cost and discomfort¹.

decision set including all possible decisions at time t . In the terminal state, the objective value $V_t(s_t)$ is calculated from the discomfort value for all states inside the state set which satisfy constraints 2.5, 2.9 and 2.12. Next, for each time slot before the initial slot, backward induction is used. For every state in a single time slot, the best decision which minimizes the discomfort and electricity cost for the current time slot plus the objective value of the next expected state by using state transition functions 2.4, 2.8, 2.11 is found. The best decision and its corresponding objective value are saved for all states at time slot t . Upon arriving to the initial time slot, the state set only contains a single state which is the current status. The best decision and its corresponding objective value are obtained by performing the same

Algorithm 1 Dynamic programming - backward induction.

Step 0.

when $t = T$

for all $s_t \in \mathbf{S}_t$ **do**

$$V_t(s_t) = \alpha_t^{\mathcal{D}} \cdot \mathcal{D}_t(s_t).$$

end for

Step 1.

when $t = T-1, T-2, \dots, 2, 1$

for all $s_t \in \mathbf{S}_t$ **do**

$$V_t(s_t) = \min_{x_t \in \mathbf{X}_t} (\alpha_t^{\mathcal{C}} \cdot \mathcal{C}_t(s_t, x_t) + \alpha_t^{\mathcal{D}} \cdot \mathcal{D}_t(s_t) + \mathbb{E}\{V_{t+1}(s_{t+1}(s_t, x_t, \tilde{u}_t))\}).$$

end for

Step 2.

when $t = 0$

$$x_t = \operatorname{argmin}_{x_t \in \mathbf{X}_t} (\alpha_t^{\mathcal{C}} \cdot \mathcal{C}_t(s_t, x_t) + \alpha_t^{\mathcal{D}} \cdot \mathcal{D}_t(s_t) + \mathbb{E}\{V_{t+1}(s_{t+1}(s_t, x_t, \tilde{u}_t))\}).$$

procedure as the step 1 in Algorithm 1. By following this algorithm, all the possible states and decisions for current and future time slots are examined to find the best decision which minimized the objective value. Also, the best decisions for states at future time slots are also obtained. The DYNAMO toolbox²⁸ used for this work gives a decision map that contains all the best decisions for all states at current and future time slots; however, when arriving at a future time slot, the information will be updated such as future outside temperature and water usage. It is better to perform optimization again rather than use the decision from old results. Therefore due to the high number of computations to be made, approximating the states and decisions for future time slots is a reasonable way to improve the DP solving time without greatly impacting its result accuracy.

Approximate dynamic programming represents a massive class of methods. We used a sample backward induction method to overcome the curses of dimensionality in DP. This method follows the same process with backward induction as previous stated; however, instead of examining every state, a subset of possible states, decisions, and stochastic variables are sampled by using Sobol sampling²⁹, and then evaluated. The decisions and objective values of unsampled states are approximated from its nearby states by using value function approximation³⁰. The ADP method is shown in Algorithm 2.

Algorithm 2 Approximate dynamic programming - sampled backward induction.

Step 0.
 when $t = T$
 $\mathbf{S}_t^* = \mathcal{F}_s(\mathbf{S}_t)$
for all $s_t^* \in \mathbf{S}_t^*$ **do**
 $V_t^*(s_t^*) = \alpha_t^{\mathcal{D}} \cdot \mathcal{D}_t(s_t^*)$.
 $\bar{V}_t \leftarrow (V_t^*(s_t^*), s_t^*)$
end for

Step 1.
 when $t = T-1, T-2, \dots, 2, 1$
 $\mathbf{S}_t^*, \mathbf{X}_t^*, \tilde{\mathbf{U}}_t^* = \mathcal{F}_s(\mathbf{S}_t, \mathbf{X}_t, \tilde{\mathbf{U}}_t)$
for all $s_t^* \in \mathbf{S}_t^*$ **do**
 $V_t^*(s_t^*) = \min_{x_t^* \in \mathbf{X}_t^*} (\alpha_t^{\mathcal{C}} \cdot \mathcal{C}_t(s_t^*, x_t^*) + \alpha_t^{\mathcal{D}} \cdot \mathcal{D}_t(s_t^*) + \mathbb{E}\{\bar{V}_{t+1}(s_{t+1}^*(s_t^*, x_t^*, \tilde{u}_t^*))\})$.
 $\bar{V}_t \leftarrow (V_t^*(s_t^*), s_t^*)$
end for

Step 2.
 when $t = 0$
 $\mathbf{X}_t^*, \tilde{\mathbf{U}}_t^* = \mathcal{F}_s(\mathbf{X}_t, \tilde{\mathbf{U}}_t)$
 $x_t = \operatorname{argmin}_{x_t^* \in \mathbf{X}_t^*} (\alpha_t^{\mathcal{C}} \cdot \mathcal{C}_t(s_t, x_t^*) + \alpha_t^{\mathcal{D}} \cdot \mathcal{D}_t(s_t) + \mathbb{E}\{\bar{V}_{t+1}(s_{t+1}^*(s_t, x_t^*, \tilde{u}_t^*))\})$.

The sampled backward induction is similar to backward induction, but includes additional sampling and value approximation steps. Sobol sampling is used as the sample function $\mathcal{F}_s$. All states in a state set at time slot t are passed into the sample function, and it returns uniformly distributed sampled states. A local average of the points within a normalized radius to construct a value function approximation is used³⁰. The k-d tree is used to store a tuple of the objective value and its corresponding state as a point-value pair. The value approximation function will estimate the objective value at any other arbitrary state (point) based on the weighted average of a neighborhood of nearby states (points). Otherwise, this entire process is similar to backward induction. In the terminal states, it samples all states $\mathbf{S}_t$ and for each sampled state s_t^* , the objective value $V_t^*(s_t^*)$ is calculated and stored in the value approximate function with its sampled state. Next, for each time slot, except the initial time, we sample states, decisions, and stochastic variables and get three sampled variable vectors $\mathbf{S}_t^*, \mathbf{X}_t^*, \tilde{\mathbf{U}}_t^*$. For each sampled state s_t^* , we find the best decision which minimizes

the objective value for the current state; however, the objective value for next state s_{t+1}^* is needed although it may be unknown. Therefore, the value function approximation is introduced in order to get an approximate objective value for the next state. Note that, for ADP-based algorithms, the core concept is how to approximate the objective value for an unsampled state. After the objective value for the current sampled state is obtained, it is stored into a value approximate function which is shown as Step 0 in Algorithm 2. The last step is to get decision variables for the initial state. Since the initial state is unique, we only need to sample its decision and uncertainty but not its state. The same procedure shown as Step 1 in Algorithm 2 is performed to find the best decision for the initial state given. In the DYNAMO toolbox, only the decision for the initial state is given rather than the whole decision tree since the states are sampled and their objective values are approximated. However, the decision for the initial state is sufficient for most cases, i.e. any other decisions or the whole decision tree is not needed. Therefore, the ADP does not calculate unnecessary information and is efficient.

2.3 Simulation Results

Table 2.2: *Simulation parameters for HVAC, WH, EV¹.*

Appliance range of operation and other Parameters		
Algorithm	DP Backward Induction	ADP Sampled Backward Induction
State Range	$\{[70,85], [108,118], [20,100]\}$	$\{[70,85], [108,118], [20,100]\}$
Stochastic Variable Range	$\{[85, 100],[0,10],[0,12]\}$	$\{[85, 100],[0,10],[0,12]\}$
Desired Values	$\{77,113,92\}$	$\{77,113,92\}$
EV Arrival/Departure Time	$\{17,9\}$	$\{17,9\}$
State Samples	3600 (Total #of States)	1200
Decision Samples	N/A	60
Uncertainty Samples	N/A	30

The HEMS model was coded in MATLAB using the standard DYNAMO toolkit problem structure, which enables solving with both DP and ADP without changes. The discomfort and cost function coefficients, α_t^D and α_t^C in the objective function were equally weighted.

HVAC parameters in the state transition expression in 2.4 were obtained by applying linear regression to a historical data set for a residential house located in Hillsboro, Oregon^{31;32}. A cooling case is studied here. WH parameters were extracted from Mathieu³³. EV battery parameters and the forecast data for outside temperature, hot water demand, and NCL were adopted from Wu et al.³². For both DP and ADP simulations, appliances range of operation and other data are summarized in Table 2.2.

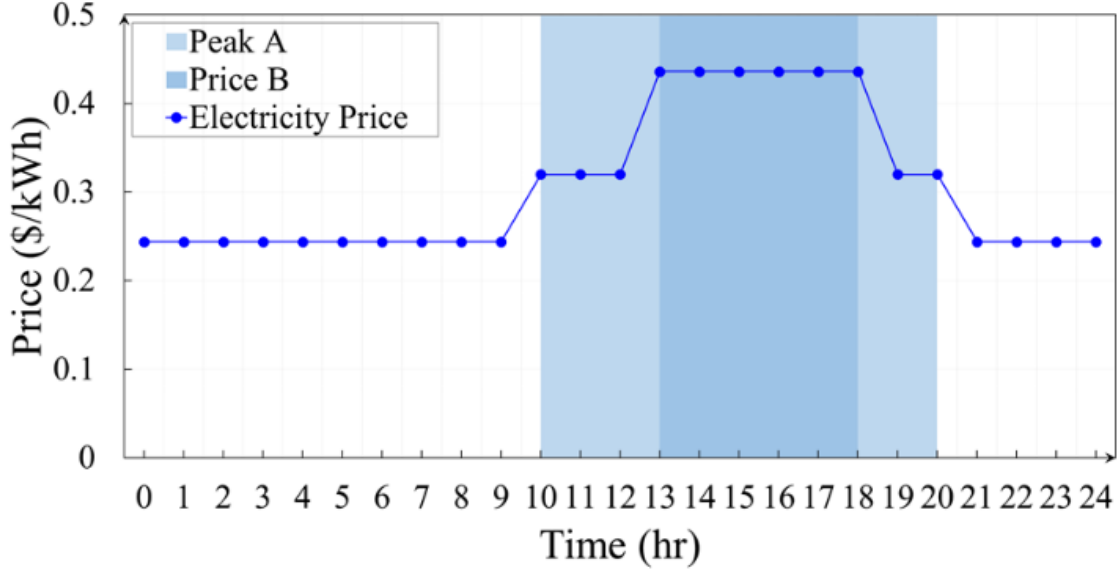


Figure 2.3: *Modified time-of-use electricity tariff¹.*

Adoption of the modified Pacific Gas & Electric (PG&E) time-of-use electricity rate, ETOU-E6 (Fig. 2.3). This plan contains three price levels: \$0.24/kWh, \$0.32/kWh, and \$0.44/kWh that are referred to as the Base, Peak A, and Peak B prices, respectively. Peak A is applied during hours 10-12, 19, and 20, and Peak B is applied during hours 13-18. In the remaining hours, Base prices are applied. Both DP and ADP compute the current decision by looking forward, and two separate cases were simulated as follows.

2.3.1 DP versus ADP Comparison

The first case was simulated to show the performance of ADP versus DP. Both DP and ADP were run ten times to optimize for the current decision by looking ahead 24 hours.

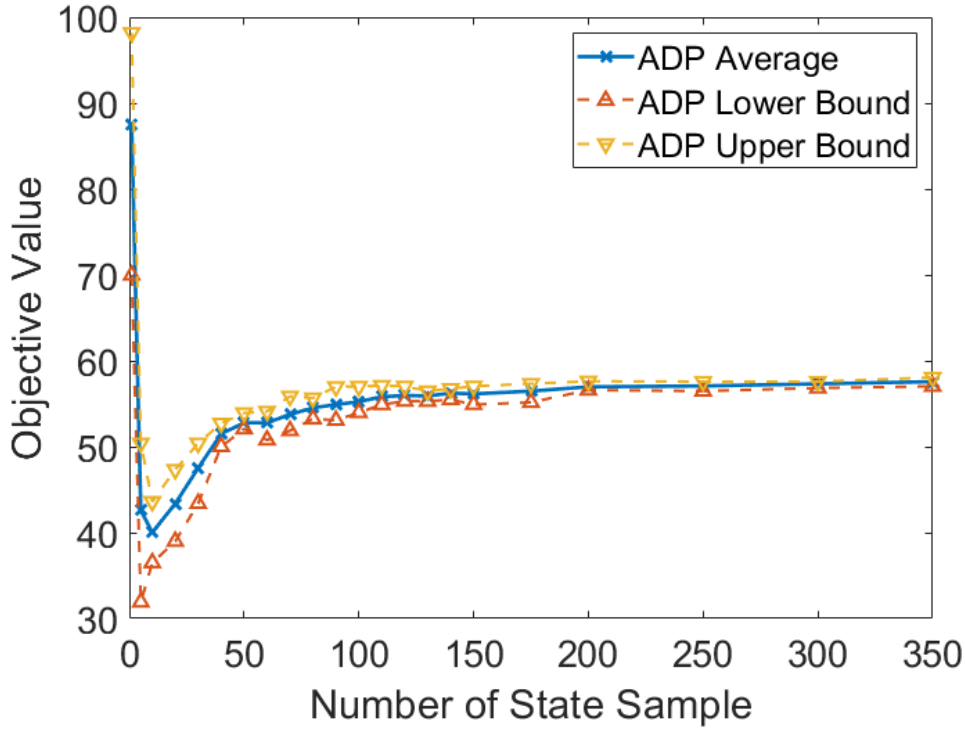


Figure 2.4: Objective value attained by ADP with increasing number of state samples when decision sample is 30.

Fig. 2.4 shows the average objective value generated by ADP with different state samplings. thirty decision samples are considered here. For each state sample, ADP runs ten times with identical settings to get the objective value and computation time. As shown in Fig. 2.4, when the number of state samples is small, the objective value fluctuates greatly. For instance, when there is only one state sample, the maximum objective value is obtained from ADP is nearly 100, and minimum is about 70. Note that, ADP will output negative objective values since approximation function is working improperly when number of state samples are small. These numbers are not considered in this case as they are valueless. Notice that increasing the number of state samples returns a more steady objective value. With 200 or more state samples, ADP returns similar decisions compared to DP. It is believed the small error in the objective value comes from the approximation function. It is worth mentioning that the small difference in the objective value does not affect the decision-making.

Table 2.3 shows the average computation time of ADP compared to DP for varying state

Table 2.3: *ADP and DP run time for different state sample sizes.*

DP	Time(s)	6642.8										
ADP	Samples #	1	5	10	20	30	50	60	70	80	90	100
	Time (s)	9.9	11.0	13.0	16.2	20.0	26.1	29.0	31.9	34.6	36.9	39.2
	Samples #	110	120	130	140	150	175	200	250	300	350	
	Time (s)	41.9	43.2	45.3	47.3	48.8	53.9	57.5	63.5	71.7	74.7	

sample sizes. Increasing the number of state samples increases the ADP computation time sublinearly, while the objective value increases rapidly at first then converges asymptotically. However, even at the maximum considered number of 350 samples, ADP still computes the decision in 74.7 seconds while DP takes nearly a hundred times longer at 6642.8 seconds. The DP solution takes longer as it exhaustively traverses the entire state, decision, and uncertainty spaces to find the optimal decision. In conclusion, ADP gets similar decisions with DP while performing much faster.

2.3.2 HEMS Scheduling Using ADP

The second case was simulated to examine the HEMS decisions for 24 hours starting at midnight. At every hour, ADP with 1200 samples and 12-hour look-ahead was implemented in a rolling window fashion to generate HVAC, WH, and EV decisions for the current time step. The results of this simulation are shown in Fig. 2.5 along with shaded regions showing Peak A and B prices. In each subplot, the horizontal dotted line shows the target state and the line graph (both solid and dotted) with square and circle markers show the HEMS-estimated state transitions as a result of the HEMS decision and stochastic variable impact. The bars at every hour show the first-hour forecast of the 12-hour look-ahead stochastic variable plus a small noise generated randomly. During each hour, there are two data points shown by a square and a circle marker representing the pre-decision and post-decision state, respectively. Each pre-decision state is connected to the post-decision state by a solid line representing the decision applied process, and each post-decision state is connected to the next pre-decision state by a dotted line representing the impact of stochastic variable on the HEMS state.

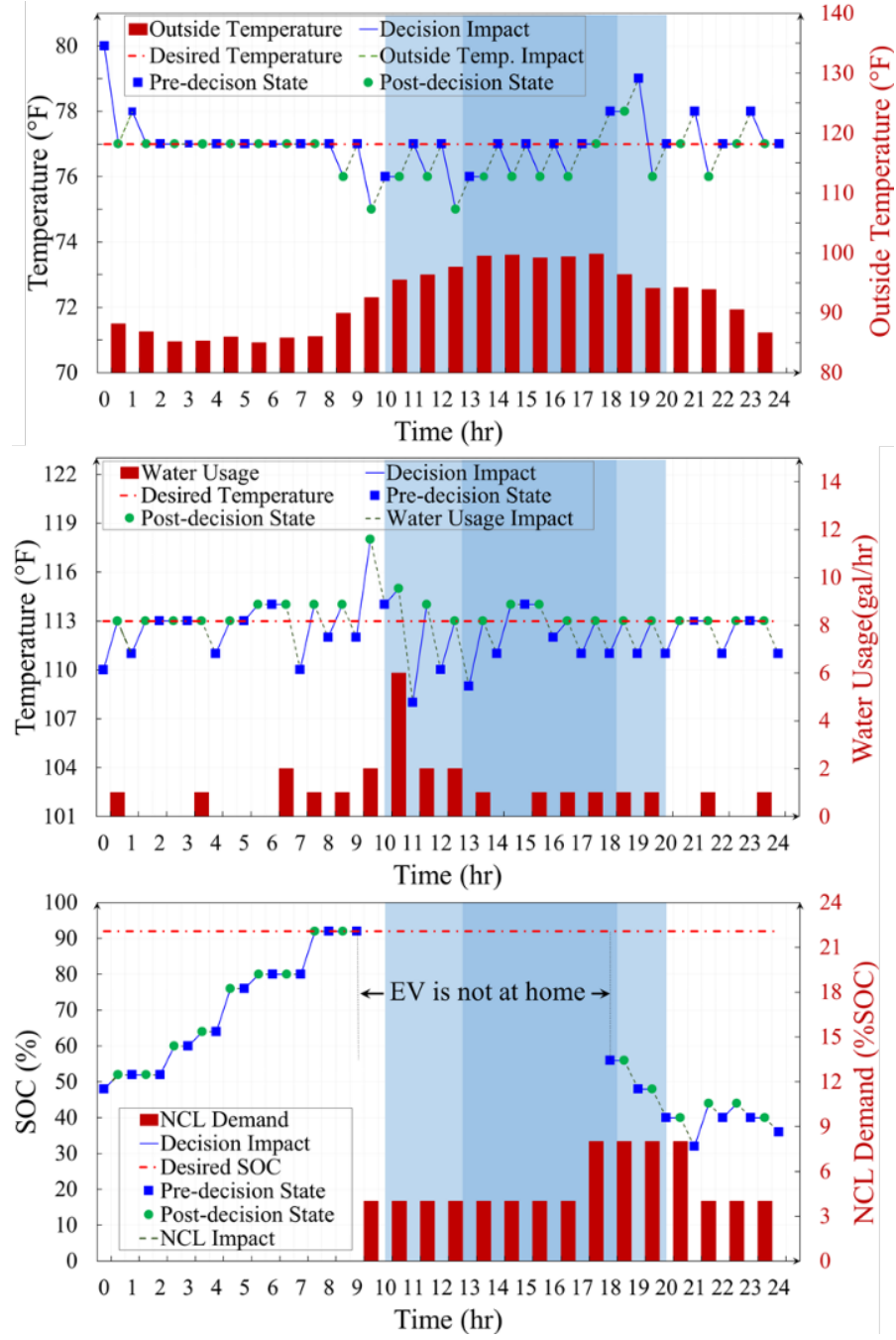


Figure 2.5: HEMS states, decisions, and uncertainty for 24 hours with a 12-hour look-ahead schedule for HVAC (Top), WH (middle), and EV (bottom)¹.

The top figure of Fig. 2.5 shows the optimal indoor air temperature determined by the HEMS on a summer day. Notice that the air temperature state fluctuates around the desired value of 77°F to minimize discomfort. There are multiple time steps at which the HEMS precools

the air temperature. For example, at hour 9, when the price is lowest, HEMS initiates precooling before the price increases to Peak A and the outside temperature increases. A similar precooling effect is observed for time step 12. Analogously, at hours 17 and 18, due to current high price and upcoming lower prices, the HEMS does not take any cooling action and allows the temperature to increase to minimize electricity cost. As soon as the price drops from Peak A level, the HEMS decides to cool the air considerably to minimize discomfort after successive hours with no cooling actions during high prices. The effect of stochastic variable realization, i.e., outside temperature is clearly seen after each decision is applied.

Similar observations can be made for WH schedules shown in middle figure of Fig. 2.5. At hour 9, the HEMS decides to preheat the water significantly in preparation for expected high demand of hot water usage and increasing price in upcoming hours. During hours with no water demand, the HEMS decides to not heat the water.

For the EV, we assume that the initial SOC is at 48% and it departs at 9 AM and arrives back to the home at 6 PM while traveling a known commuting distance that reduces the SOC by 36%. The bottom figure of Fig. 2.5 shows that the deviation from the desired SOC is high during hours other than the departure time. This is because the discomfort due to EV SOC is applied only at the departure time, i.e., no penalty is applied for deviation from the desired SOC when the EV is parked at home. Notice that, the HEMS decides to charge the EV to meet the desired SOC at the departure time. When driving, the SOC drops according to the driving distance and the efficiency of the EV battery. Since the EV arrives home during Peak A prices, the HEMS postpones charging until the lower price hours. When the price is high, the EV will discharge to serve the uncontrollable load.

2.4 Summary

Based on the numerical results, ADP offers a promising approach to the HEMS-based appliance scheduling under uncertainty. In particular, a proper selection in the number of state samples used in sampled backward induction can provide a very near optimal solution

compared with DP while using significantly less computation time. Further computational savings can be achieved with a slight compromise in solution accuracy. Also, the ADP based HEMS avoids the high electricity cost and maintains the user comfort using methods such as pre-cooling the room or pre-heating the water.

Chapter 3

ADP versus MILP Comparison

3.1 Related Work

A variety of mathematical models and solution algorithms for HEMS using mixed-integer linear programming (MILP) are proposed^{34–40}. Bozchalui et al.³⁴ proposed a deterministic MILP model while considering end-user preferences. The uncertainty associated with weather forecasting, non-controllable loads, and electricity prices poses an additional dimension of complexity in HEMS. Chen et al.³⁵ used a scenario-based Monte Carlo simulation by considering real-time electricity price as uncertainty. Conejo et al.³⁶ applied robust optimization techniques to model the price uncertainty. Hubert and Grijalva³⁷ proposed a residential electricity consumption management, which uses a robust optimization approach to minimize the impact of uncertainty in stochastic inputs. To make a trade-off between electricity costs and uncertainties of inputs, Wu et al.³⁸ used conditional value-at-risk for the real-time scheduling of appliances in HEMS. Chen et al.³⁹ proposed a new energy efficient scheduling algorithm to minimize the monetary expense of the household based on the time-varying price model. To adjust the deterministic solution, an energy consumption adaptation variable is utilized to accommodate the stochastic energy consumption patterns. Yu et al.⁴⁰ proposed an approach of modeling and optimizing stochastic HEMS by classifying different types of loads, where the kind of loads are HVAC, plug-in hybrid EV, and

deferrable loads such as washers and dryers.

MILP and ADP are two primary methods to solve the HEMS problem. However, there is a very limited body of work comparing both algorithms in the context of home energy management system. Keerthisinghe et al.⁴¹ proposed an ADP based HEMS to optimize PV-storage system. Also, it compares the performance of DP/ADP and MILP. However, these models or algorithms do not use the same mathematical formula and have not taken into account either major appliances or large state sets for ADP.

In this section, ADP and MILP algorithms are evaluated in the same structure, and these methods employ the same mathematical formula to model and solve the HEMS problem. The HEMS schedules multiple appliances and determines set points for the HVAC and the water heater, and the charge schedule for an electric vehicle. The HEMS minimizes expected cost and discomfort to the household, under a range of uncertainties. These algorithms are evaluated in respect to computation time and solution quality. To our best knowledge, this work is the first of its kind to compare the two algorithms in the HEMS consisting of multiple major appliances.

3.2 Problem Formulation

MILP formulation is composed of the objective function and constraints. A Markov state transition function, an objective function and constraints are used for DP to model the problem. Since the MILP can directly adopt linear equations, the same mathematical formulations are used for both methods as shown in Chapter 2. There is a small change for HEMS compared with Chapter 2. The EV battery does not serve the uncontrollable load and never discharges so there is no uncertainty for the EV.

The deterministic case of MILP can be formulated and solved using equations 2.1- 2.13 since all equations are linear. Unlike the deterministic case, a large set of scenarios generation and reduction methods are needed in stochastic MILP in order to incorporate with the stochastic variable like outside temperature. The scenarios are sampled from the range of stochastic variables and follow a normal distribution. Scenario reduction methods choose a subset from

all scenarios based on a probability metric⁴². Simultaneous backward reduction is used in this case. It calculates the probability metric and combines two scenarios with the closest value. Since each scenario has its own decision, two-stage decision variables are used in the stochastic MILP model. The first stage decisions, which are here-and-now decisions, are in the binding intervals. All here-and-now decisions should be the same in all scenarios since they should be performed immediately before the realization of uncertainties. However, the second stage wait-and-see decisions are in the look-ahead intervals. They can be varied for different scenarios.

3.3 Model Predictive Control

Model predictive control framework is used for testing the efficacy of the ADP and the MILP. Based on the concept of MPC, the simulation for all methods is described in Algorithm 3.

Algorithm 3 MPC-based simulation framework.

Step 0.

At time t , update the initial status of each appliance: s_t^{HVAC} , s_t^{WH} , s_t^{EV} , and new forecast data: $\tilde{u}_t^{OUT}$, $\tilde{u}_t^{WH}$.

Step 1.

If stochastic MILP is considered, generate a large set of scenarios based on new forecast data, and apply simultaneous backward reduction method to reduce the number of scenarios as needed.

Step 2.

Run a single method and get the current decisions for each appliance: x_t^{HVAC} , x_t^{WH} , x_t^{EV} .

Step 3.

Run the simulation and gather next hour status of each appliance based on the current decision.

Step 4.

Go back to Step 0, and increase t to $t+1$ until simulation ends.

In each simulation, every method looks ahead a certain number of hours and gets decisions for each hour. Note that, ADP only outputs current hour decisions but still considers all

look-ahead hours like other methods. However, MPC only uses decisions for the current hour and update the next hour status of each appliance.

3.4 Simulation Results

MPC-based co-simulation framework is proposed in this thesis. Fig. 3.1 shows the diagram of this framework.

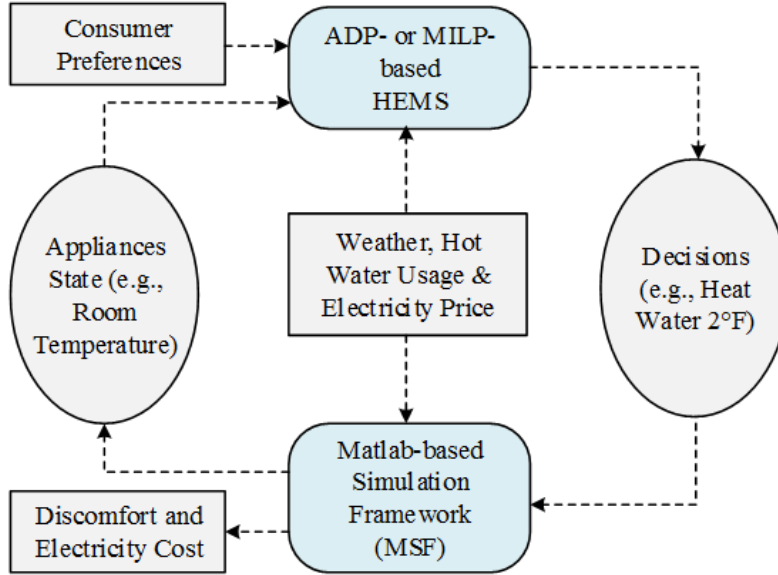


Figure 3.1: *Diagram of co-simulation framework.*

The ADP based HEMS model was coded in MATLAB using the standard DYNAMO toolkit problem structure, which enables solving with ADP. We selected a local average as an approximation function for ADP, which was explained in Chapter 2. Since the DYNAMO toolkit provides parallel computing ability for ADP, 12 cores are used for running the ADP method. The MILP based HEMS was coded in the General Algebraic Modeling System (GAMS), and it is solved by the CPLEX solver with a 1% optimality gap. The consumer preferences are discomfort and cost function coefficients, α_t^D and α_t^C in the objective function which is Equation 2.1. Weather, hot water usage and electricity price are provided to both HEMS and the Matlab-based simulation framework (MSF). Both HEMS methods will

perform optimization and give the decisions to the MSF. Based on the decisions and actual data, such as outside temperature, the solver calculates the discomfort value, electricity cost, and appliances state for the next hour. All appliances states, such as room temperature, will be used as inputs for HEMS for the next hour optimization. Inside each HEMS, the HVAC parameters in the state transition expression in 2.4 were obtained by applying linear regression to a historical data set for a residential house located in Hillsboro, Oregon^{31;32}. A cooling case is studied here. WH parameters were extracted from Mathieu³³. EV battery parameters and the forecast data for outside temperature and hot water demand were adopted from Wu et al.³². For ADP and MILP simulations, appliances range and other variables are summarized in Table 3.1.

Table 3.1: *Appliances range and other variables.*

Appliances range and other variables			
Appliances	HVAC(°F)	WH(°F)	EV(%SOC)
State Range	[70,85]	[108,125]	[20,100]
Decision Range	[-4,0]	[0,6]	[0,12]
Stochastic Variable Range	[60,110]	[0,10]	N/A
Desired Value	75	113	92
State Resolution(ADP)	0.1	1	4

We adopt the Pacific Gas & Electric (PG&E) time-of-use electricity rate, ETOU-E6 (Fig. 3.2). This plan contains three price levels: \$0.244/kWh, \$0.32/kWh, and \$0.436/kWh that are referred to as the Base, Peak A, and Peak B prices. Peak A is applied during hours 11-13, 20, and 21, and Peak B is applied during hours 14-19. In the remaining hours, base prices are applied.

The HEMS decisions for 24 hours starting at midnight are simulated and examined here. At each hour, both methods with 12-hour look-ahead were implemented in a rolling window fashion to generate HVAC, WH, and EV decisions for the current time step. Eight hundred state samples out of 57,078 states and 80 decision samples out of 1,148 decisions are used for ADP. In order to measure the performances of the ADP and MILP, we develop three cases as follows:

1. Deterministic MILP and ADP with perfect forecast.

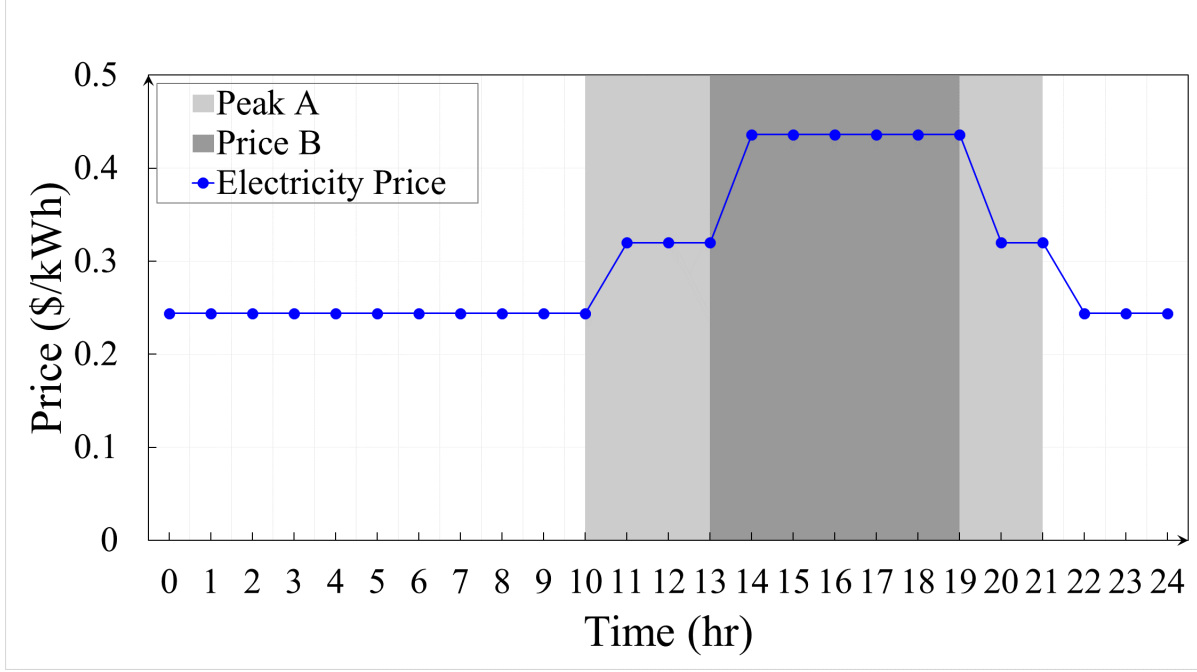


Figure 3.2: *The time of use electricity tariff.*

2. Deterministic MILP and ADP with inaccurate forecast
3. Stochastic MILP and ADP with inaccurate forecast.

In the first case, forecast values are considered as the only scenario in the deterministic MILP and ADP. Also, the forecasted outside temperature and water usage are taken as actual outside temperature and water usage at each hour in the MPC co-simulation framework, that is, perfect forecasting is considered. The second case simulates inaccurate forecast, where the actual outside temperature and water usage for each hour in the simulation framework are randomly sampled using a normal distribution with forecasted temperature and water usage as mean. The standard deviations of HVAC and water usage are 3% and 10% of their respective means. Stochastic MILP and ADP are considered in the third case. Ten thousand scenarios were randomly generated by normal distribution for stochastic MILP, with means and standard deviations the same as those in the second case. Three thousand scenarios were obtained after applying scenarios reduction method. In the stochastic ADP, the same normal distribution is also used to get the probability for each random state to facilitate comparison. All three cases are simulated to examine the HEMS decisions for 24

hours starting at midnight. At every hour, the ADP and the MILP both look 12-hour ahead and only implement HVAC, WH, and EV decisions for the current time step.

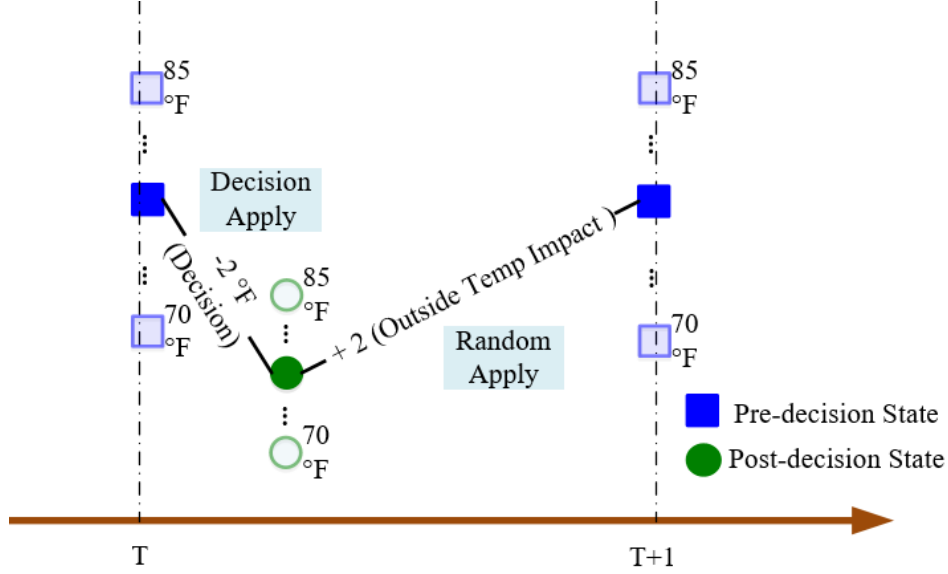


Figure 3.3: *Illustration of results.*

In order to compare both methods and show the results clearly, we developed a way to show the scheduling, as shown in Fig. 3.3 by adopting the dynamic programming algorithm. HVAC is shown as an example in this case. There are two data points shown by a square and a circle marker representing pre-decision and post-decision state, respectively. The square marker is the pre-decision state in the dynamic programming language. In this case, it is the initial room temperature of time T or the temperature at the end of time $T-1$. Each pre-decision state is connected to the post-decision state by a solid line representing decision impact. This process is called decision application. It shows the decision made by HEMS, which is the number of $^\circ\text{F}$ the room temperature will decrease, i.e. x_t^{HVAC} , in this case. Each post-decision state is connected to the next pre-decision state by a solid line representing a stochastic variable, i.e. $\tilde{u}_t^{OUT}$. This is the process of random application. In this way, the graph clearly shows the decisions and appliance states for each time slot.

The simulation results of deterministic HEMS with inaccurate forecast along with shaded regions showing Peak A and B prices are shown in Fig. 3.4. In each subplot, the horizontal

dotted line shows the target state, and the blue and red line show the MILP and ADP results from the simulation framework as stated above, respectively. The bar at each hour shows the first hour forecast of the 12-hour look ahead stochastic variable plus a small noise generated randomly by using a normal distribution with forecast temperature and water usage as means.

Table 3.2 shows each component and total objective value from simulation framework for both methods and the running time.

Table 3.2: *ADP and MILP objective value and running time.*

	<i>Method</i>	Deterministic perfect forecast	Deterministic inaccurate forecast	Stochastic inaccurate forecast
HVAC cost (\$)	<i>MILP</i> <i>ADP</i>	36.29 34.23	37.85 35.79	37.68 36.43
Water heater cost (\$)	<i>MILP</i> <i>ADP</i>	7.11 7.08	7.64 7.72	7.68 7.72
Electric vehicle cost (\$)	<i>MILP</i> <i>ADP</i>	3.95 3.95	3.95 3.95	3.95 4.83
HVAC discomfort	<i>MILP</i> <i>ADP</i>	1.10 5.07	3.41 5.36	3.58 5.91
Water heater discomfort	<i>MILP</i> <i>ADP</i>	1.34 4.84	2.19 5.02	2.24 5.82
Total objective value	<i>MILP</i> <i>ADP</i>	49.80 55.17	55.04 57.83	55.13 60.69
Running time(s)	<i>MILP</i> <i>ADP</i>	31.52 27770.07	32.17 26389.23	8927.21 38226.2

As shown in Fig. 3.4, both methods give similar decisions and results, and their objective values are close, as shown in Table 3.2. The bottom figure of Fig. 3.4 shows the EV SOC for the case of charging. We assume that the initial SOC is at 56% and the EV departs at 3 PM and arrives back at 8 PM while traveling a known commuting distance that reduces the SOC by 36%. The reason behind this EV schedule is to examine whether or not each method avoids the peak price and charges the EV in advance. In the Table 3.2, the EV charging cost for each method is the same except in the stochastic case since the ADP charges the EV to 100% which is above the desired SOC. One possible reason is the set of decisions that

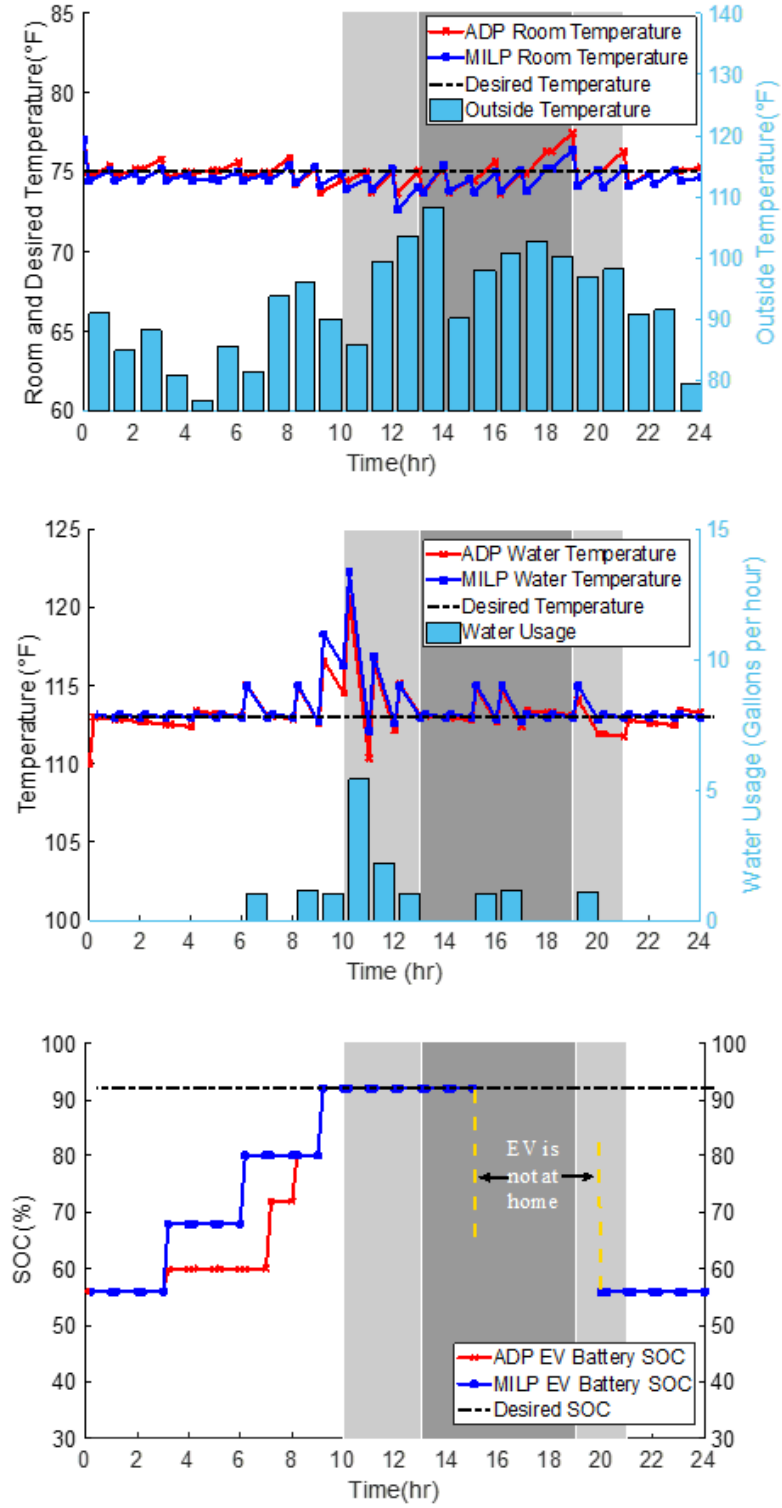


Figure 3.4: Result for deterministic HEMS with inaccurate forecast for HVAC (top), WH(middle), and EV(bottom).

are sampled at each time slot and it may not have a no charge option at certain time slots. Also, there not a constraint or penalty when the SOC is above the desired value. Even when the cost is increased, all charge actions take place during low price times. From the bottom figure of Fig. 3.4, both methods charge the EV in advance and meet the desired value at the departure time. Note that, discomfort due to EV SOC is applied only at the departure time, i.e., no penalty is applied for deviation from the desired SOC when the EV is parked at home.

The top figure of Fig. 3.4 shows the room temperature for the case of cooling. Notice that the air temperature fluctuates around the desired value of 77 °F to minimize discomfort. At hour 12, when the price is lowest, both methods initiate pre-cooling before prices increase to Peak A and the outside temperature increases. Analogously, at hour 18, due to the current high electricity rate and upcoming lower prices, both methods do not take any cooling action and let the temperature increase to minimize electricity costs. As soon as the price drops from Peak A level, they opt to cool the air considerably to reduce discomfort after consecutive hours with no cooling actions during higher prices. Similar observations can be made for the WH schedules shown in the middle figure of Fig. 3.4. At hour 9, both methods decide to preheat the water temperature significantly in preparation for expected high demand and price in upcoming hours. During hours with no water demand, the HEMS chooses to maintain the water temperature. However, the difference in the objective values for the two methods shown in Table 3.2 mainly comes from the discomfort term. ADP has less accurate control to maintain the water temperature compared to MILP from hours 0 to 4, shown in the middle figure of Fig. 3.4. MILP can meet the desired water temperature, i.e., 113°F, at every hour. The ADP state resolution of water heater temperature is 1°F, when no decision is made, and no hot water is used, the actual water heater temperature in the co-simulation drops by 0.15°F after one hour, according to thermal dynamic phenomenon modeled Equation 2.8. Thus, due to rounding, it will take 4 hours for the ADP to notice there is a 1°F temperature drop. This explains why, as seen in the middle figure of Fig. 3.4, the ADP decides to heat water at hour 5 rather than during previous hours as the MILP solver does. However, if we increase state resolution of the ADP, it will mitigate this situation.

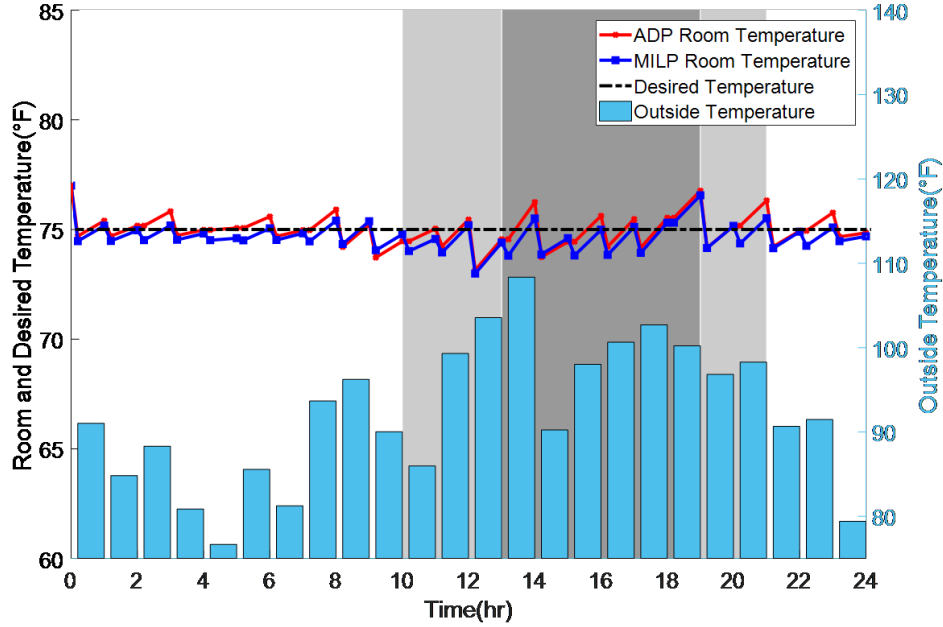


Figure 3.5: HVAC result for stochastic HEMS with an inaccurate forecast.

It is interesting to compare the deterministic and stochastic case to elucidate the benefit of using stochastic HEMS. By comparing the top figure of Fig. 3.4 and 3.5, both methods make similar decisions. However, if we compare the objective value of stochastic MILP and ADP in Table 3.2, the stochastic case is even slightly higher than that of the deterministic case. It shows the impact of the stochasticity is quite small and even negative sometimes. This is because stochastic HEMS has many scenarios to be considered and the stochastic variable has little weight in thermal equations. For the stochastic outside temperature, even if there exists a 10 °F forecast error, it is only a 0.5 °F difference in thermal dynamic Equation 2.4. Also, the MPC framework, on its own, has the capability to deal with the forecast error by updating the forecasts repeatedly over the time horizon.

By comparing the running time for both methods in Table 3.2, the MILP is much faster than ADP. However, it is worth mentioning that unlike the MILP, a critical feature of ADP/DP is that it is easy to introduce non-linearity in the objective function and/or constraints. However, this is out of the scope of this thesis and will be studied in the context of non-

linear HEMS model in our future work; for example, taking into account non-linear thermal discomfort and higher-order thermal dynamic equations.

3.5 Conclusion

ADP and MILP in both deterministic and stochastic applications can effectively solve the HEMS problem. The MILP and the ADP lead to similar decisions and appliance schedules. However, ADP has less accurate control on the room and water temperature, resulting in a higher objective value due to increased discomfort. One of main reasons for this is the discretization of the state, decision and uncertainty space in the ADP. However, the ADP demonstrates several advantages over the MILP, one being that it is easy to introduce nonlinearity in all the model functions including objective, state transition, and constraints. Also, we found that stochastic impact is quite trivial or even negative in the ADP and MILP since stochastic variables have small weights in thermal dynamic equations. In addition, the MPC framework, on its own, has the capability to deal with the forecast errors by updating the forecasts repeatedly over the simulation horizon.

Future work will look into a non-linear HEMS model, e.g., non-linear thermal discomfort and higher-order thermal dynamics, and compare these two methods. Since the number of states in ADP increase exponentially with the addition of appliances, we plan to uncouple all appliances and run ADP for each appliance in parallel. This will allow increased state resolution and number of appliances while avoiding a combinatorial explosion in the number of states.

Chapter 4

HEMS-Enabled Transactive Flexibility in Real-Time Operation of Three-Phase Unbalanced Distribution Systems

Previous chapters state the HEMS can balance the user discomfort and electricity cost based on the current and future electricity price and stochastic variables. If we consider a broader picture of the distribution system, HEMS can be also used as a demand response (DR) resource to benefit the distribution system while potentially increasing users' revenue. This chapter discovers a coordinated, two-stage, real-time market mechanism that HEMS, as the DR resource, can effectively alleviate line congestions, voltage violations, and substation-level power imbalances. This chapter requires knowledge in distribution system to understand the proposed mechanism, which will be briefly presented in the following subsections. More details can be found in our publication².

Table 4.1: *Notation*²

$i, j, \phi, 0$	Index of node, line, phase, and substation
h, a, t	Index of home, appliance, and timeslot
$\mathcal{N}_N, \mathcal{N}_L, \mathcal{N}_\phi$	Set of nodes, lines, and phases
$\mathcal{N}_{F+}, \mathcal{N}_{F-}$	Set of nodes with, and without flexibility
$\mathcal{N}_H, \mathcal{N}_A, \mathcal{N}_T$	Set of homes, appliances, timeslots
V, p, q	Voltage, real, reactive power injections
c^G, c^D	Generation cost, demand value
λ, π	Substation node price (LMP), DLMP
ν, δ	Value of lost load, congestion penalty
ψ, η	Penalty factor, scalar in the range [0,1]
κ, f	Line overload coefficient, slack variable
$\tilde{\cdot}, \check{\cdot}$	Indicate stochastic variable, curtailment
$\underline{\cdot}, \overline{\cdot}$	Indicate lower, upper bounds

4.1 Introduction and Related Work

In recent years, distribution systems have experienced unprecedented growth in the deployment of distributed energy resources (DERs) including PV-equipped homes and smart homes. The distribution system market is anticipated to undergo a fundamental restructuring towards a transactive energy market due to increasing availability and active role of economically rational DER owners³ and their participation in DR programs. As a consequence of this transformation, new market pricing mechanisms that can facilitate the efficient and reliable operation of the grid are being investigated. In this line of research, pricing based on distribution locational marginal price (DLMP) is widely being studied and proposed^{43–50}. However, it has been shown in several studies that adopting such market-based mechanisms in a distribution system with a high deployment of price-responsive DERs can adversely affect the distribution system operation by causing congestions^{43;51}. It is therefore crucial for a distribution system operator (DSO) to design congestion mitigation strategies in three-phase unbalanced distribution systems and coordinate with the way flexibility service is utilized from price-responsive end users.

Contrary to the transmission system, distribution systems are highly unbalanced and have higher losses and voltage drops due to higher r/x (resistance/reactance) ratio. A few stud-

ies have incorporated power flow constraints to obtain losses, voltage violations, and line congestion prices using DLMP decomposition^{47;48;50}. In these studies, the appearance of voltage violation and congestion components in a nodal DLMP indicates the occurrence of an operational issue, partially caused by the marginal contribution of the nodal demand. It is hence beneficial to both the DSO and a price-responsive end user, such as a smart home operated by a HEMS^{32;52;53} to alleviate any violation or congestion by providing some flexibility service in real-time. To the best of our knowledge, there is no framework in the literature that can enhance the DSO's real-time market operation as well as add operational reliability and value through coordinated utilization of flexibility service from HEMSs.

A few other related papers that deal with real-time HEMS-based DR are reported^{54–58}. Althaher et al.⁵⁴ proposed an optimization-based control of deferrable loads by HEMS in response to real-time pricing signals with the goal of reducing consumer's electricity bills while minimizing the total daily curtailment of load. Tsui and Chan⁵⁵ proposed another HEMS-level DR optimization framework under real-time pricing that uses convex programming to relax integer variables to continuous ones for the efficient and flexible incorporation of multiple deferrable loads. Mohsenian-rad and Leon-garcia⁵⁶ proposed a home-level consumption scheduling framework which attempts to achieve a desired tradeoff between minimizing electricity payment due to real-time pricing and minimizing waiting time for the operation of each appliance. Shareef et al.⁵⁷ surveyed additional literature on HEMS-enabled DR based on real-time pricing. Unfortunately, none of the above papers and the references therein study a real-time coordinated mechanism between the DSO, which prices customers according to a state-of-the-art method (DLMP), and HEMS in an unbalanced distribution system. The closest study to our work is the work of Siano and Sarno⁵⁸, which assesses the benefits of residential DR in real-time distribution markets based on DLMP. However, this work mostly focus on the benefits of DR to the grid and assume a balanced distribution system without dealing with any coordination mechanism between the DSO and the residential customers. In this chapter, a DLMP-based real-time operational framework for the DSO to operate unbalanced three-phase distribution systems in a congestion-free manner by procuring a coordinated flexibility service from HEMS is proposed. The HEMS is assumed to interact

with the DSO and provide its optimal flexibility range by minimizing the household’s total expected cost and discomfort considering the current state of controllable appliances and their uncertain future demand.

4.2 Framework

We consider an unbalanced distribution system that serves a different number of homes in each phase of its three-phase nodes (see Fig. 4.3). We assume that homes on every phase are of either regular or smart (HEMS-equipped) type. A smart home has been considered to own PV panels coupled with ES (battery storage), HVAC, WH, and NCL that are entirely controlled by its HEMS (see Fig. 4.2).

To determine if there is any congestion or voltage violation on the grid, we model the DSO to initially implement a reliability assessment by solving a first-stage optimization problem based on real-time nodal demand bids from loads and supply bids from distributed generation (DG), if any, at the three-phase feeder level, e.g., each of the 68 nodes in Fig. 4.3. The DSO can, however, solve its first stage optimization problem without any need for demand or supply bids, and can maximize the social welfare by dispatching as much power as demanded and allowed by the grid constraints. The DLMP values that are each composed of energy, losses, congestion, and voltage violation components are computed using the first-stage optimization solution and sensitivity analysis. When congestion or voltage violation prices are seen, the DSO realizes the existence of an operational issue and immediately seeks flexibility service from HEMS to alleviate them while maintaining a three-phase power-balance at the substation node. By using DLMP components, the DSO can send two price (a lower and an upper) signals to each HEMS and inquire a flexible demand range.

In the next step, each HEMS can compute and send the inquired demand range (flexibility) to the DSO by incorporating the DSO’s prices in its ADP-based stochastic optimization problem and finding optimal consumption amounts (demand) of its controllable appliances. In the second stage, by aggregating the flexibility ranges of all the participating HEMS, the DSO can determine an optimal dispatch point without any distribution system congestion

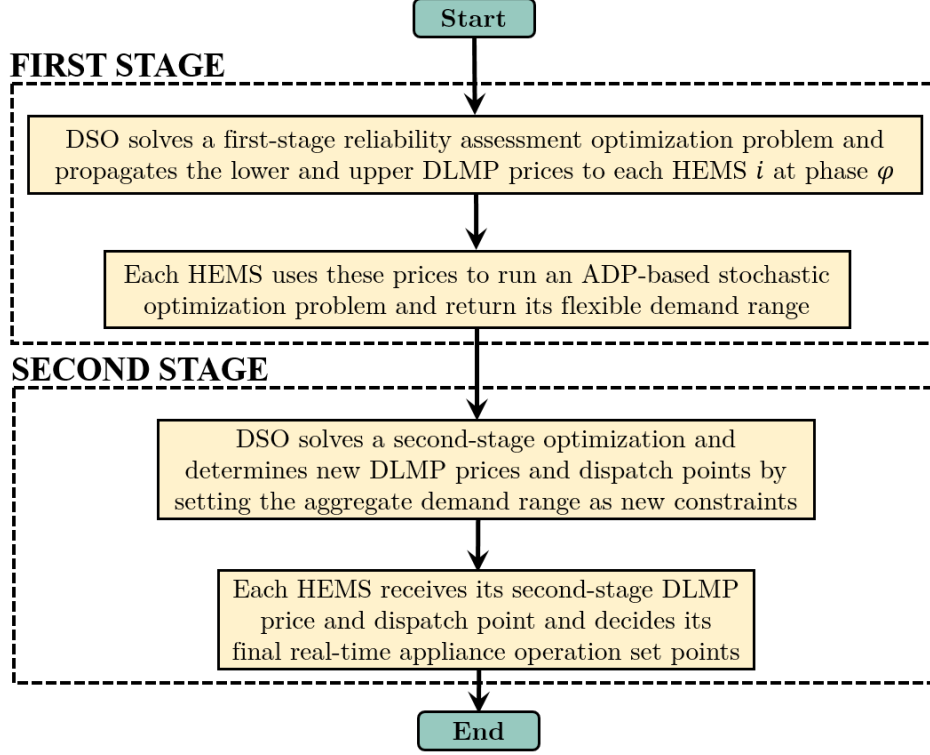


Figure 4.1: *Flowchart of the proposed two-stage framework².*

or voltage violation and send it back to each HEMS. In its second stage, each HEMS sets the dispatch point as the maximum consumption for its controllable appliances. The flowchart in Fig. 4.1 summarizes the above procedure.

4.3 System Model

4.3.1 DSO's first-stage optimization problem

The DSO's first-stage optimization problem can be formulated as in 4.1, which minimizes the objective function by dispatching the least cost generation, considering high-value load and avoiding curtailment. The first-term, $\lambda_0^p \cdot p_0^\phi$, represents cost for wholesale supply and the third term, $c_i^{G,\phi} \cdot p_i^{G,\phi}$, represents the cost for DG supply. The cost for curtailment is shown in the second term, $\nu^p \cdot \tilde{p}_i^{D,\phi}$. The fourth term, $c_i^{D,\phi} \cdot p_i^{D,\phi}$, gives the incentive to serve the high-value load. There are also line, voltage, and other constraints associated with

Equation 4.1 in order to model power flow. This is not shown it as it is out of the scope of this thesis. More detail can be found in the publication².

$$\text{Minimize:} \sum_{p_0^\phi, p_i^{G,\phi}, p_i^{D,\phi}, \tilde{p}_i^{D,\phi}} \sum_{i \in \mathcal{N}_N, \phi \in \mathcal{N}_\phi} \left(\lambda_0^p \cdot p_0^\phi + \nu^p \cdot \tilde{p}_i^{D,\phi} + c_i^{G,\phi} \cdot p_i^{G,\phi} - c_i^{D,\phi} \cdot p_i^{D,\phi} \right) \quad (4.1)$$

4.3.2 DLMP Computation Using Sensitivity Analysis

DLMP is an important part of our first-stage problem. We need to use the DLMP as a demand response signal to the HEMS. The real power DLMP, $\pi_{p,i}^\phi$, in phase ϕ of each three-phase distribution node i is defined as the sum of the energy price, $\pi_{p,0}^{E,\phi}$, the price of losses, $\pi_{p,i}^{L,\phi}$, the price of voltage violations, $\pi_{p,i}^{V,\phi}$, and the price of line congestions, $\pi_{p,i}^{C,\phi}$, caused by the incremental dispatch in phase ϕ of node i . When needed, the reactive power DLMP, $\pi_{q,i}^\phi$, is similarly defined as the sum of its corresponding components in phase ϕ of node i . More details can be found in the publication².

4.3.3 HEMS First-Stage Optimization Problem

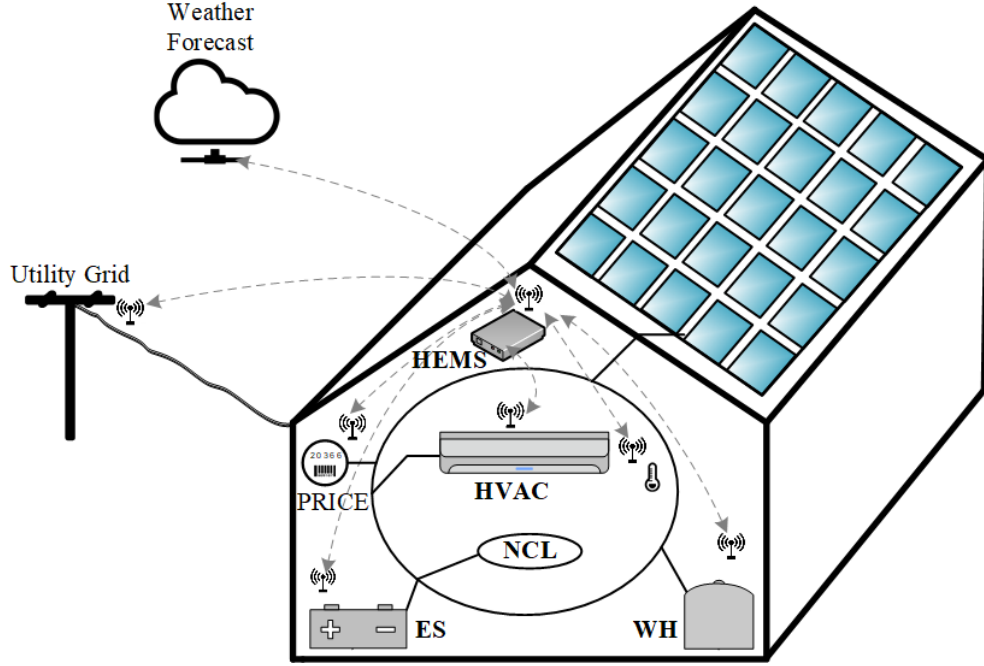


Figure 4.2: *HEMS illustration for a PV-equipped home with ES and major loads, i.e. HVAC, WH, and NCL².*

The system used here is the same as in Section 2.1. We minimize the electricity cost and user discomfort by using lower and upper DLMPs given by the DSO. However, we consider that each HEMS has its own PV-panels coupled with an ES unit and non-controllable loads. Additionally, each house also has HVAC and WH units. A new schematic of such a house is shown in Figure 4.2. The equations for these devices can be found in Section 2.1. Note that, previously our decisions for each appliance is temperature or SOC. However, this method does not work well in this system because total electricity usage must be constrained, as shown in Equation 4.9. It is hard to generate a decision set if temperature or SOC is used as the decision. Therefore, in this model, the decision is changed to energy and a parameter, γ_E , is used as a unit conversion coefficient which converts energy to temperature or SOC. The new state transition equation for HVAC and WH units will be:

$$s_t^{\text{HVAC}} = \begin{cases} \gamma^{\text{RM}} s_{t-1}^{\text{HVAC}} - \gamma_E^{\text{HVAC}} x_t^{\text{HVAC}} + \gamma^{\text{OUT}} \tilde{u}_t^{\text{OUT}}, & \text{if cooling} \\ \gamma^{\text{RM}} s_{t-1}^{\text{HVAC}} + \gamma_E^{\text{HVAC}} x_t^{\text{HVAC}} + \gamma^{\text{OUT}} \tilde{u}_t^{\text{OUT}}, & \text{if heating} \end{cases} \quad (4.2)$$

$$s_t^{\text{WH}} = \gamma^{\text{WH,C}} s_{t-1}^{\text{WH}} + \gamma_E^{\text{WH}} x_t^{\text{WH}} - \gamma^{\text{USG}} \tilde{u}_t^{\text{WH}} \Delta t \quad (4.3)$$

The total energy consumption will be:

$$\mathcal{P}_t^{\text{G}} = x_t^{\text{HVAC}} + x_t^{\text{WH}} + x_t^{\text{ES}} \quad (4.4)$$

Since we have two DLMP prices for our optimization problem, we will solve the HEMS problem twice by using the upper and lower price $[\underline{\pi}_{p,i}^\phi, \bar{\pi}_{p,i}^\phi]$. Therefore, we will get our lower and upper flexible range $[\underline{p}_h^\phi, \bar{p}_h^\phi]$ for each HEMS home located in phase ϕ .

With $\mathcal{N}_{H^+}^{i,\phi}$ and $\mathcal{N}_{H^-}^{i,\phi}$ showing the sets of homes with and without HEMS in phase ϕ of node i , the total net demand, $p_i^{D,\phi}$, in phase ϕ of the three-phase node i can be computed by summing p_h^ϕ over all homes h , $\forall h \in \{\mathcal{N}_{H^+}^{i,\phi} \cup \mathcal{N}_{H^-}^{i,\phi}\}$. For regular homes, p_h^ϕ represents the real-time fixed demand of home h .

$$p_i^{D,\phi} = \sum_{h \in \mathcal{N}_{H^+}^{i,\phi}} p_h^\phi + \sum_{h \in \mathcal{N}_{H^-}^{i,\phi}} p_h^\phi \quad (4.5)$$

Hence, the flexibility range $[\underline{p}_i^{D,\phi}, \bar{p}_i^{D,\phi}]$ can be determined using $[\underline{p}_h^\phi, \bar{p}_h^\phi]$ in the first term of Equation 4.5.

4.3.4 DSO's second stage optimization problem

$$\textbf{Minimize:} \sum_{p_0^\phi, p_i^{D,\phi}, \tilde{p}_i^{D,\phi}} \left(\lambda_0^p \cdot p_0^\phi + \nu^p \cdot \tilde{p}_i^{D,\phi} + c_i^{G,\phi} \cdot p_i^{G,\phi} - c_i^{D,\phi} \cdot p_i^{D,\phi} \right) + \sum_{j \in \mathcal{N}_{\text{LC}}, \phi \in \mathcal{N}_\phi} \psi \cdot f_j^\phi \quad (4.6)$$

The objective function 4.1 from the first-stage has been modified to include a penalty term $\sum \psi \cdot f_j^\phi$, where ψ shows a large number to highly penalize congested lines, as shown in Equation 4.6. Here, $\mathcal{N}_{\text{LC}}$ shows the set of congested lines in the first-stage. By using a

slack variable, f_j^ϕ , line flow can be allowed up to a certain overload coefficient (κ) of the line capacity, e.g. $\kappa = 0.9$ limits the line flow to a maximum of 90% of the line capacity. By finding an optimal solution, $p_i^{D^*,\phi}$ in the range $[\underline{p}_i^{D,\phi}, \bar{p}_i^{D,\phi}]$ and $\pi_{p,i}^{\phi*}$ in the range $[\pi_{p,i}^\phi, \bar{\pi}_{p,i}^\phi]$, the second-stage optimization problem can completely remove the congestion and voltage violation components of the DLMP.

The DSO's second-stage solution, $p_i^{D^*,\phi}$, is the optimal dispatch in phase ϕ of the three-phase node i which serves a large number of HEMS-equipped ($h \in \mathcal{N}_{H+}^{i,\phi}$) and regular ($h \in \mathcal{N}_{H-}^{i,\phi}$) homes in each phase. As the last step of the proposed method, the question now is how to redistribute the optimal dispatch point, $p_i^{D^*,\phi}$, among HEMS-equipped homes in each phase. Here, a convex combination is used to redistribute the three-phase dispatches to each HEMS-equipped home. Without loss of generality, it is assumed that the flexible portion of $p_i^{D^*,\phi}$ coming from HEMS-equipped homes is the convex combination of their flexibility range endpoints at the three-phase node level, and compute a scalar value $\eta \in [0, 1]$ according to the following linear combination.

$$\left(p_i^{D^*,\phi} - \sum_{h \in \mathcal{N}_{H-}^{i,\phi}} p_h^\phi \right) = \eta \cdot \left(\bar{p}_i^{D,\phi} - \sum_{h \in \mathcal{N}_{H-}^{i,\phi}} p_h^\phi \right) + (1 - \eta) \cdot \left(\underline{p}_i^{D,\phi} - \sum_{h \in \mathcal{N}_{H-}^{i,\phi}} p_h^\phi \right) \quad (4.7)$$

Note that, when all homes in phase ϕ of node i are HEMS-equipped, then $\sum_{h \in \mathcal{N}_{H-}^{i,\phi}} p_h^\phi = 0$. Next, the computed η and the lower and upper flexibility range of each HEMS-equipped home are used to find its maximum consumption amount, $p_h^{\phi*}$.

$$p_h^{\phi*} = \eta \cdot \underline{p}_h^\phi + (1 - \eta) \cdot \bar{p}_h^\phi \quad (4.8)$$

4.3.5 HEMS Second Stage Optimization Problem

In this stage, the same thing is solved with the previous one by using actual DLMP given by the DSO. However, the consumption amount, $p_h^{\phi*}$, must be used, which is calculated in the second-stage optimization problem as the upper limit of energy consumption.

$$\mathcal{P}_t^G = x_t^{\text{HVAC}} + x_t^{\text{WH}} + x_t^{\text{ES}} \leq p_h^{\phi*} \quad (4.9)$$

With the flowchart shown in Fig. 4.1, the Algorithm 4 provides a detailed summary of the overall two-stage mechanism.

Algorithm 4 Two-Stage Algorithm².

Step 0.

Solve Equation 4.1 according to Section 4.3.1, compute and determine $[\pi_{p,i}^\phi, \bar{\pi}_{p,i}^\phi]$ according to Section 4.3.2 at the DSO-level and send it to each HEMS (**first-stage DSO optimization**).

Step 1.

Use $[\pi_{p,i}^\phi, \bar{\pi}_{p,i}^\phi]$ to solve HEMS problem twice and compute $[\underline{p}_h^\phi, \bar{p}_h^\phi]$ according to Equation 4.4 for each HEMS and send it to DSO (**first-stage HEMS optimization**).

Step 2.

3. Use Equation 4.5 to compute the flexibility range, $[\underline{p}_i^{D,\phi}, \bar{p}_i^{D,\phi}]$, of each three-phase node. Solve 4.6, and determine each three-phase node's dispatch point and price, $[p_i^{D*,\phi}, \pi_{p,i}^{\phi*}]$. Then, use Equation 4.7 and Equation 4.8 to determine HEMS-level dispatch point, $p_h^{\phi*}$. Send $p_h^{\phi*}$ and $\pi_{p,i}^{\phi*}$ to each HEMS (**second-stage DSO optimization**).

Step 3.

Use $p_h^{\phi*}$ and $\pi_{p,i}^{\phi*}$ to solve each HEMS problem with constraint 4.9 to determine final appliance decisions and HEMS-level dispatch points (**second-stage HEMS optimization**).

4.4 Simulation Results

The proposed two-stage mechanism was implemented on a modified IEEE 69-node distribution system, as shown in Fig. 4.3, using CPLEX and the ADP functionality in DYNAMO toolkit. In Fig. 4.3, the unbalanced three-phase loads are shown by arrows and their corresponding real-time bids were set in a way to create line congestions and voltage violations in the first stage. Each node's three-phase load was assumed to be the aggregate load of the homes connected to the respective phase. Two types of homes, regular homes (without HEMS) and smart homes (HEMS-equipped), were considered. A regular home is assumed passive whose real-time demand has to be served under any circumstance. A HEMS-equipped home is assumed to have the willingness to respond to the pricing signals from the DSO, provide a flexibility range, and adjust its controllable load (HVAC, WH, and ES) consumption.

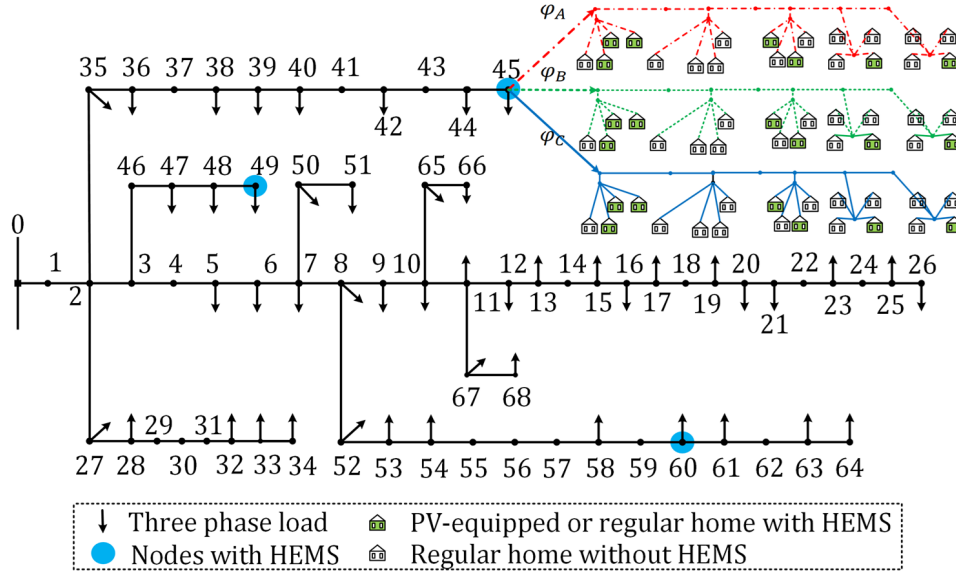


Figure 4.3: One line diagram of the 69-bus system with HEMS-equipped homes at nodes 45, 49, 60, and regular homes elsewhere².

The simulation setup in this section is designed in a way to first specify the most vulnerable lines and nodes that are prone to congestion and voltage violations. Then, HEMS-equipped homes were considered as the nodes with the highest demand along the specified congested lines. In our case study, the real-time demand and bids of the three-phase nodes in the

system create line congestions in lines 2 (the line connecting node 1 to 2), 35, 46, and 52, and voltage violations in nodes 26, and 60-64. With the highest three phase loads located at nodes 45, 49, and 60, different numbers of HEMS-equipped homes were considered at these nodes (shown by blue circles).

Table 4.2: *Number of HEMS-equipped homes of type I, II, and III in each phase of nodes 45, 49, and 60².*

Node index	45	49	60
# of type I HEMS	20	18	40
# of type II HEMS	6	1	5
# of type III HEMS	4	1	5
Total # of HEMS	30	20	50

Furthermore, with everything else being identical and HVAC composing the major portion of its load, each HEMS-equipped home was classified to type I, II, and III according to their initial (real-time) room temperatures. Without loss of generality in specifying the types of homes, we consider initial room temperatures of $76^{\circ}F$, $79^{\circ}F$, and $82^{\circ}F$ to denote types I, II, and III, respectively. The goal here is twofold. First, observe how each sample HEMS type provides flexibility by taking the DSO's price and the occupants discomfort into consideration while being at different discomfort levels due to differing initial room temperatures. This aspect of the work is quite novel in the sense that it provides a way for an active consumer (HEMS-equipped home) to respond to the DSO's price signal and provide DR under real-time circumstances while accounting for household's discomfort. Second, evaluate the impact of the flexibility provided by HEMS in bringing operational benefits to the grid.

Table 4.2 summarizes the number of sample HEMS types placed at nodes 45, 49, and 60. Here, the number of regular homes has been considered zero to provide high flexibility. Also, for each phase, the same number of each HEMS type has been considered.

For the three types of homes, all HEMS related parameters used in simulating the ADP-based stochastic optimization problem have been tabulated in Table 4.3.

Next, for conciseness and better illustration, the simulation results of the DSO's first and second-stage optimization problems are presented. Then, the first and second-stage HEMS-level results of three home types for HVAC are presented. Further, as a sample case for

Table 4.3: *Parameters used in the ADP-based HEMS stochastic optimization².*

Parameters	HVAC	WH	ES
State range ($^{\circ}\text{F}$, $^{\circ}\text{F}$, %)	[70,80]	[108,125]	[20,100]
Desired Temp/minimum SOC ($^{\circ}\text{F}$, $^{\circ}\text{F}$, %)	75	113	20
Decision range ($^{\circ}\text{F}$, $^{\circ}\text{F}$, %)	[0,4]	[0,6]	[0,12]
Uncertainty range($^{\circ}\text{F}$, $^{\circ}\text{F}$, %)	[60,110]	[0,10]	[0,12]
Energy needed (kWh/ $^{\circ}\text{F}$, %)	5.3	0.72	0.5
State resolution ($^{\circ}\text{F}$, $^{\circ}\text{F}$, %)	0.1	1	2
Discomfort coefficients (β)	1.05	0.4	2
HEMS type I, II, III initial state ($^{\circ}\text{F}$, $^{\circ}\text{F}$, %)	[76,79,82]	[113,113,113]	[36,36,36]

HEMS type III, scheduling results for the WH and ES are shown.

4.4.1 Result for DSO First and Second Stage Optimization Problem

The simulation results of the DSO's first and second stage optimizations are shown in Figure 4.4. Only phase B is used to show the simulation results of the DSO's first and second-stage optimization problem. The other two phases have similar results which shown in the paper². The top figure of Fig. 4.4 shows the DLMP values (prices), whereas the middle and bottom figures of Fig. 4.4 show physical grid quantities (power flow, line limits, etc). In the top figure of Fig. 4.4, the DLMP values and their components are stacked and shown for both (before and after HEMS flexibility) stages. We first focus on the first stage.

The DLMP values of the first stage, shown by the red line, are very high. The first stage DLMPs are composed of energy price (dark green fill), loss price (light green fill), nonzero voltage violation price (dark orange fill), and nonzero line congestion price (light orange fill). The physical grid quantity counterparts of the first stage DLMPs are shown by a red line for each line's MVA flow in the middle figure of Fig. 4.4 and each node's voltage magnitude in the bottom figure of Fig. 4.4. The green dotted lines in the middle and bottom figure show each line's MVA limit and normal voltage operation limits respectively. Note that, at some lines (e.g., lines 1 and 2), the red line (first stage quantities) overlaps and hides the dotted green lines (limits). Moreover, it can be observed that as a result of flow congestion

in lines 2, 35, 46, and 52, and voltage violation in node 26 (red lines hitting the limit), their corresponding DLMP components are activated in the top figure of Fig. 4.4. Notice that a congestion/voltage violation in one line/node adds the corresponding DLMP component not only to that line/node but also to the lines and nodes that are affected by it, or share a line in its route to the substation node. For instance, again in phase B, node 26 has a voltage violation, so the price is reflected mainly on nodes 1-26, as well as other nodes affected.

In the second stage, when HEMS-equipped homes in nodes 45, 49, and 60 provide flexibility, it is seen in Fig. 4.4, that the congestion and voltage violation components of the DLMPs (the light and dark orange fills) have completely vanished - reducing it to mere energy and loss prices. The obvious reason is that none of the black graphs in middle and bottom figures of Fig. 4.4 hit a limit. Note that this is due to the penalty term in the DSO's second stage objective function to relax the congested line loading to within κ (0.95 in our simulation) multiplies of its capacity.

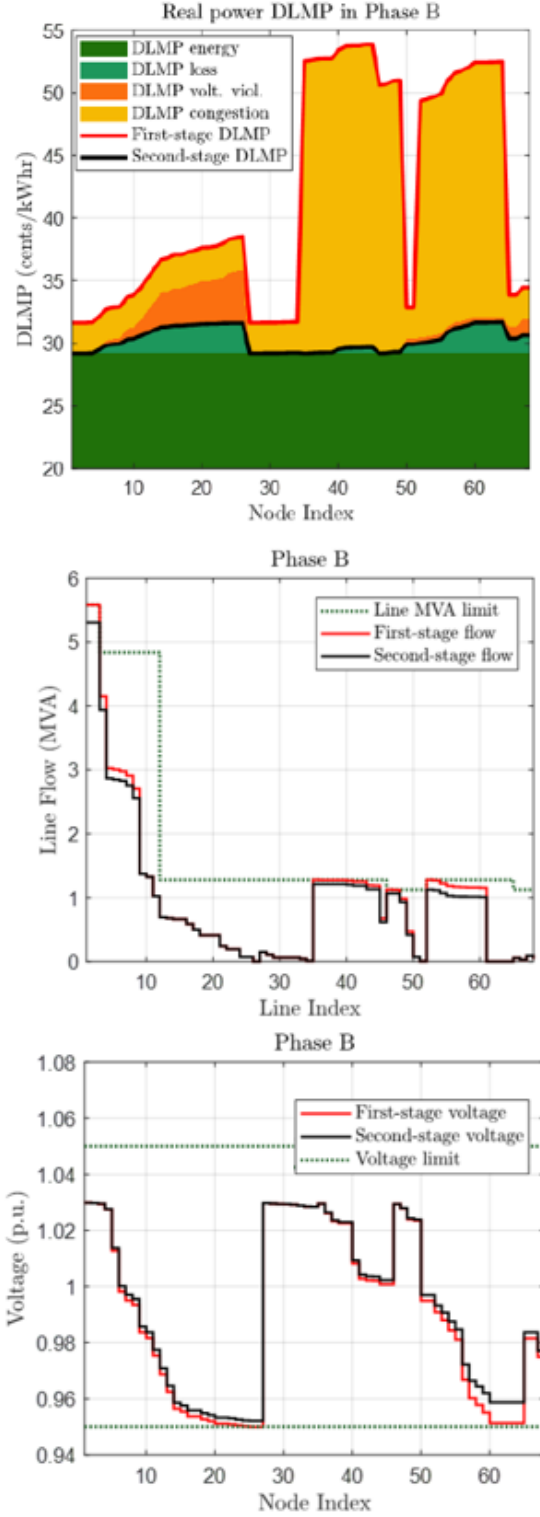


Figure 4.4: Result of DSO's problem for real power DLMP (top), line MVA flow (middle) and node voltage (bottom) of phase B².

Table 4.4: *Flexibility in kW used by the DSO in each phase of nodes 45, 49, and 60².*

Flexibility by:	Phase A	Phase B	Phase C
Node 45 (kW)	47.7	47.7	47.7
Node 49 (kW)	31.6	42.7	42.7
Node 60 (kW)	120.9	110.7	57.4
Total (kW)	200.2	201.1	147.8
Losses avoided (kW)	12.1	11.2	6.3

Further note that, while keeping the dispatches of the nodes without HEMS fixed, the improvement in removing the violations has been caused by only the flexibility provided at nodes 45, 49, and 60.

The aggregate amounts of three-phase flexibility provided by nodes 45, 49, and 60, as well as their total, and the resulting reduction in system losses are reported in Table 4.4. Notice that, despite the assumption of the same type and number of HEMS in each phase of these nodes, the flexibility used across their phases is different. The reason for this difference is noted as the variation across three-phase aggregate bid values of these nodes in the DSO's second stage objective function in Equation 4.6. In other words, less flexibility has been utilized from nodes with higher demand bid values - hence maximizing the resulting social welfare. This distinction makes this study interesting in the sense that it is realistically applicable to a transactive unbalanced DSO market with random real-time demand variation and bids across phases.

4.4.2 Results for HEMS Optimization Problem

The ADP-based HEMS-level results of the first and second-stage optimization is shown in Fig. 4.5 and 4.6. Here, it is assumed that the HEMS minimizes its expected cost and discomfort by looking forward into the future uncertainty space in order to make an optimal real-time (here-and-now) decision in response to the DSO's price signals. In Fig. 4.5, the top plot shows a rolling-window scheduling of the HVAC for each HEMS type for 6 consecutive timeslots while looking 6 hours into the future at each individual timeslot. Note that,

although most of the focus will be on the first timeslot, the next five hour's schedules are also plotted to show the effectiveness of HEMS decision-making under future uncertainty. The horizontal dotted line shows the desired room temperature state and the blue stairs graph shows the price of energy; the first hour is the second stage DLMP, $\pi_{p,i}^{\phi*}$, and the following hours are forecasted prices by HEMS. The height of the red shade at the end of the first timeslot shows the appliance-level flexibility range provided by the HVAC in response to the DSO's upper and lower prices, $[\pi_{p,i}^{\phi}, \bar{\pi}_{p,i}^{\phi}]$, in the first stage. Notice that the shaded flexibility range in each HEMS type is different - narrower when the initial temperature is far from its desired state (e.g., HEMS III) and wider when it is closer (e.g., HEMS I). This observation can be explained as the direct artifact of the initial room temperature and the way cost and discomfort are weighted in the objective function. HEMS type III's HVAC, which is at an initial high temperature of 82 °F (farthest from the desired temperature of 75 °F), does not provide much flexibility in response to DSO's price signals as the discomfort coefficient has a greater weight here. As an intermediate case, HEMS II shows some amount of flexibility in its tradeoff between discomfort and cost as it is closer to the desired temperature.

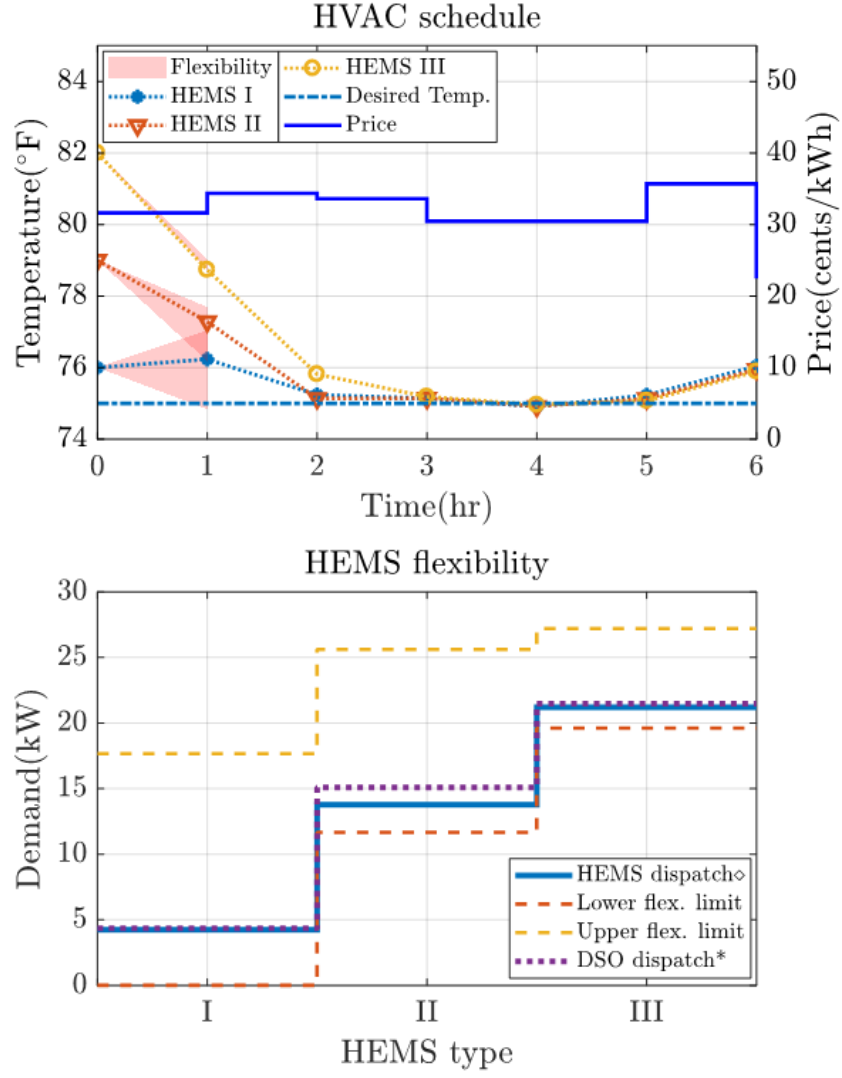


Figure 4.5: HEMS-level simulation results for home types I, II, III. The top plot shows flexibility coming from HVAC based on initial room temperature. The bottom plot shows the total flexibility coming from HVAC, WH, and ES².

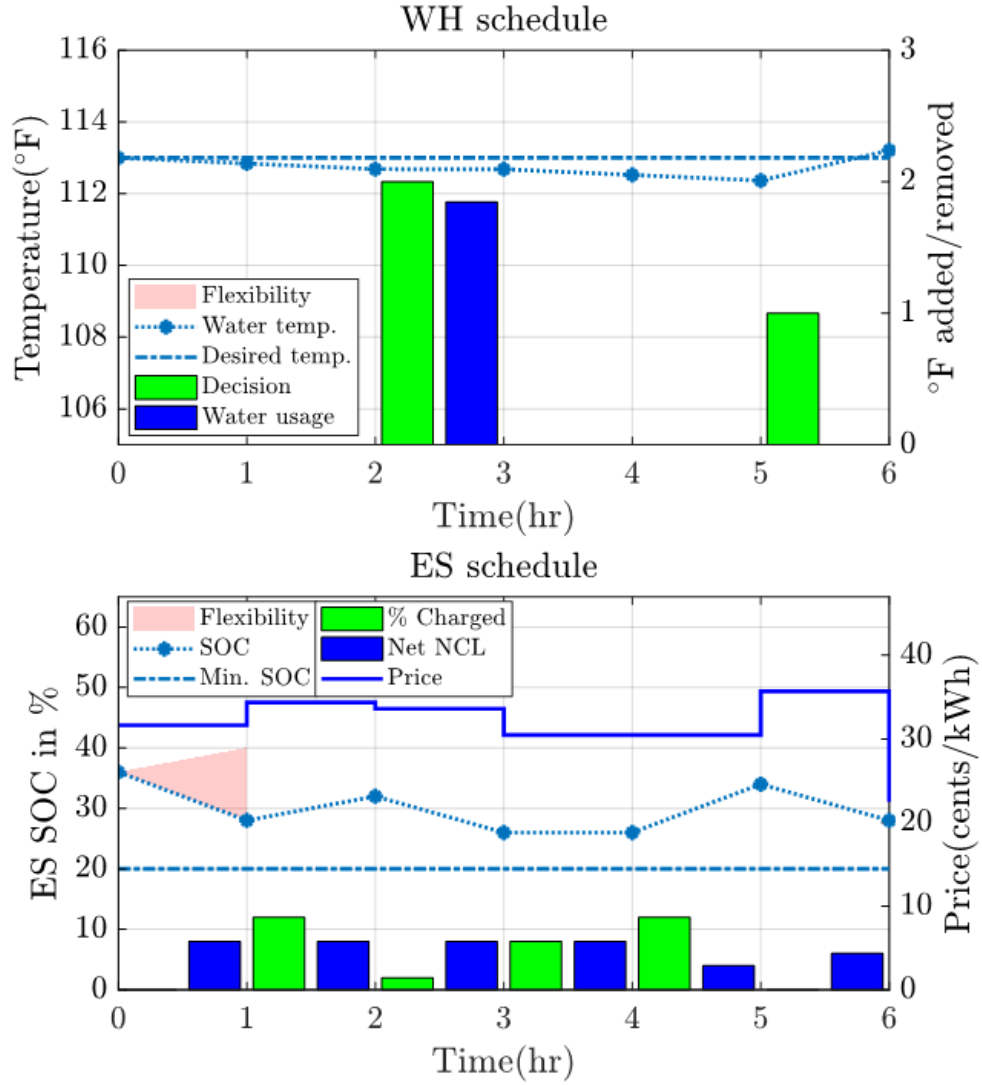


Figure 4.6: HEMS-level simulation results for WH (top) and ES (bottom). Since identical WH and ES units are considered, this plot is the same for HEMS type I, II, and III².

The graphs with markers in Fig 4.5 show the room temperature state set by HEMS at the end of its second stage optimization. Here, during each timeslot, e.g., '0-1', HEMS makes a decision whether to set the room for cooling. The temperature state transits from time '0' to '1' (the next timeslot's pre-decision state) by readily implementing the decision and applying the effect of the stochastic variable (outside temperature) over the duration of the timeslot. Notice that, because of high discomfort at 82 °F, HEMS III decides to cool the room at a

maximum rate (i.e., hits the lower bound of its tiny flexibility range with a highly negative slope) in order to get closer to the desired temperature state of 75 °F. In contrast to HEMS III, HEMS I decides to cool the room slightly. The net effect of this slight cooling decision and the stochastic outside temperature is seen as a small temperature increase above 76 °F at time '1' (slight positive slope). HEMS II, which is at an initial room temperature of 79 °F, decides to cool the room at an intermediate rate compared to HEMS I and III. In this case, the net effect of cooling decision and the outside temperature is seen as a cooling temperature amount added (negative slope). The reduction in demand coming from HVAC can be seen as the gap between the lower range of the shaded flexibility region and the marker point at time '1'. In other words, due to high initial room temperature (high discomfort), only HEMS III denies to provide any flexibility in its HVAC.

For each HEMS type, the total flexibility limits in the first-stage and the total HEMS and DSO's second-stage dispatches are shown in the bottom plot of Fig. 4.5. Here, the first stage lower and upper flexibility limits, $[\underline{p}_h^\phi, \bar{p}_h^\phi]$, are shown by the dashed lines. The DSO's second stage dispatch, $p_h^{\phi*}$, is shown by the dotted line. The final HEMS dispatch, $p_t^{h\diamond}$, is shown by the solid line. From the solid lines, it can be seen that HEMS I's demand is significantly less compared to II and III. While HEMS I and III almost hit the DSO's dispatch, HEMS II decides differently and picks a point lower than the DSO's dispatch. The reason for this decision depends on the initial room temperature state and the tradeoff between the total expected cost and discomfort over the forward-looking horizon. Note that, the second stage HEMS dispatch, $p_t^{h\diamond}$, also depends on the dispatch points of its HVAC, WH and ES.

Figure 4.6 shows the identical WH and ES results in HEMS types I, II, and III. In the top plot (for WH), the graph with markers show water temperature state transition, green bars show the equivalent water temperature in °F added (HEMS decision), and blue bars show the equivalent water temperature removed due to hot water usage (stochastic variable). The values corresponding to the bars are shown on the right vertical axis. In the bottom plot (for ES), the decision and effect of NCL (stochastic variable) is shown in equivalent %SOC added and removed respectively. Note that the net NCL was defined as non-controllable household demand minus PV generation. The state transition as the difference of the two bars are

shown by the line with markers.

In HEMS type III, while the HVAC does not provide any flexibility, its ES is set to provide full flexibility (hits the lower limit of its shaded region) by drawing zero power and serving the NCL by discharging the battery. Similarly, the WH in HEMS III (as well as in I and II) shows full flexibility as it happens to have no water usage demand (hence no shaded flexibility region) at the first timeslot due to zero water usage. In other words, the total flexibility provided by HEMS III is merely coming from ES. The kW amount of this flexibility can be readily seen as the difference (gap) between HEMS dispatch (solid line) and the upper flexibility limit (dashed yellow line) in the bottom plot of Fig. 4.5. Notice that this gap is relatively large for HEMS I and II compared to III. The reason is the additional amount of flexibility provided by HEMS I and II's HVAC.

4.5 Conclusion

Validated by the simulation results presented in the previous section, this chapter presented a two stage, real-time, and social-welfare-maximizing operation of three-phase unbalanced distribution systems through HEMS-enabled flexibility. The proposed two-stage mechanism mitigates distribution system operational issues such as line congestions and voltage violations by enabling HEMS as a demand response device. While achieving both DSO and HEMS-level objectives, it was shown that by implementing the proposed framework, flexibility service from HEMS-level appliances can be efficiently acquired.

Chapter 5

Conclusion and Future Work

5.1 Conclusion

In this thesis, an ADP-based home energy management system is developed and an evaluation of its performance is performed. Its performance is compared with another mainstream algorithm and its application in a distribution system is explored. In Chapter 2, dynamic programming is adopted to model and formulate the problem using both DP and ADP to solve the problem. It turns out that ADP offers a promising approach to solve HEMS-based appliance scheduling problem under uncertainty. Also, by carefully selecting the number of states, decisions and uncertainty samples, ADP can provide a result very close to DP by using significantly less computation time. In Chapter 3, ADP is compared with another popular algorithm in HEMS area MILP. Model predictive control based simulation framework is developed to evaluate these two algorithms and simulated using three different cases. The results show that ADP and MILP make similar decisions in all three cases. Also, the stochastic impact of the three appliances evaluated in HEMS is quite small since the stochastic variables have small weights and the MPC framework has the capability to deal with the stochastic errors. In Chapter 4, the HEMS contribution for distribution system is discovered. A coordinated two-stage real-time market mechanism is developed by utilizing the flexibility provided by HEMS to alleviate line congestions, voltage violations, and substation-level

power imbalances. The results show that HEMS can provide effective flexibility to the DSO, while considering the user's comfort.

5.2 Future Work

In this section, future research in the HEMS field is discussed. Currently, the HEMS defined in this thesis has three appliances. An addition of more appliances, such as clothes washer/dryer, dish washer, photovoltaic etc, can be explored. Those appliances will also bring non-linearity into our ADP model, which in turn highlights a significant advantage of ADP over its MILP counterpart in modeling and solving non-linear systems. Based on the results of Chapter 3, even if the ADP is much faster than the DP, it still suffers the curses of dimensionality. To overcome this difficulty, a decomposition framework decoupling all appliances to solve the optimization problem of each appliance individually and then coordinating all solution of individual appliances will be evaluated. This approach can remarkably decrease the computation time and provide the ADP with additional capabilities to account for more appliances and/or increase the fidelity of appliance models. At the time of this writing, development of a graphical user interface (GUI) for our HEMS is also underway. In the future, extension of the GUI can be applied to DP and ADP in order to run and show our results in a user-friendly manner.

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