A Data-Driven Electric Water Heater Scheduling and Control System

Gulai Shen, Zachary E. Lee, Ali Amadeh, K. Max Zhang*

Sibley School of Mechanical and Aerospace Engineering, Cornell University, Ithaca, NY 14853, USA

Abstract

Domestic hot water (DHW) heating accounts for up to 30% of average household energy use. Compared to gas fired water heaters, electric water heaters (EWH) can be powered by renewable generation resources, thus making it a potential renewable heating option. Furthermore, with the growing need for energy storage, incorporation of renewable resources, and initiatives worldwide, the electrification of DHW heating is expected to continue the rapid growth. However, many commercial EWH products with monitoring and alerting functionalities lack the intelligence to optimize and perform predictive control with data; on the other hand, research studies with refined models and simulations come short in incorporating real-time data and providing robust optimal controls under uncertainties in real-world settings. This paper presents a EWH Smart Scheduling and Control System using data-driven disturbance forecasts in a robust Model Predictive Control (MPC) to accomplish various demand side management objectives. Testing with a real-world EWH dataset and a two-state EWH model, prediction uncertainty is quantified an included in robust MPC simulations are conducted on a central EWH supplying DHW for a multi-unit apartment building. Results show that the proposed system is capable of anticipating DHW demand with an uncertainty interval covering up to 97% of the actual demand during the test days and reducing electricity cost up to 33.2% as well as maintaining a desired DHW temperature without affecting user comfort. Further, the flexibility of the system to alter load profiles under different Demand Response (DR) programs are demonstrated. Reductions in both power and gross consumption can be accomplished. The proposed system can create an implementable solution of forecasting DHW usage and optimizing controls as a part of a robust and reliable building energy management and control system in real-world settings.

Nomenclature

Δt Control time interval s

$\dot{M}_{\text{w}}$ Hot water demand m^3/s

$\dot{Q}_{\text{demand}}$ Heat loss due to demand of hot water W

$\dot{Q}_{\text{gen}}$ Heat generation from power input W

$\dot{Q}_{\text{loss}}$ Heat loss from water to ambient environment W

η Rated efficiency of water heater

*Corresponding author: kz33@cornell.edu

A Surface area of water heater m^2

C_{off} Off peak electricity price $\$/kWh$

C_{on} On peak electricity price $\$/kWh$

c_{p} Isobaric specific heat of water $kJ/(kgK)$

P Rated power consumption of water heater W

Pe Penalty during Demand Response period $\$/W$

Pe_1 Unit penalty for violation in magnitude of temperature $\$/^{\circ}C$

Pe_2 Unit penalty for violation in duration of time $\$/s$

Pe_{vio} Comfort violation penalty \$

R Thermal resistance of the water tank $(m^2K)/W$

S_i State of water heater, binaryon/off)

T_{a} Ambient temperature $^{\circ}C$

$T_{\text{h},i}$ Hot water temperature at ith time step $^{\circ}C$

T_{ini} Initial hot water temperature $^{\circ}C$

T_{in} Supply domestic cold water temperature $^{\circ}C$

T_{low} Lower limit of hot water temperature $^{\circ}C$

T_{up} Upper limit of hot water temperature $^{\circ}C$

T_{vio} Temperature magnitude violation $^{\circ}C$

t_{vio} Time duration of violation s

1. Introduction

According to the 2015 Resident Energy Consumption Survey (RECS) [1], Domestic Hot Water (DHW) provision consumes about 17.9 GJ of primary energy in the U.S., making it the second largest end-use category in home energy use after space heating. The 2015 RECS also estimated that around 16% of the average U.S. household's energy expenditure is for water heating. Apart from energy consumption, DHW usage accounts for a sizable part of total water usage in residential and commercial buildings. For example, an average person in North America uses around 64 liters of hot water per day with typically higher usage during winters and lower usage during summers [2].

Ranked by fuel types, natural gas, electricity (either through resistance heaters or heat pumps), propane, and fuel oil are the main sources of energy for providing DHW [1]. With various initiatives worldwide to decarbonize energy systems, the electrification of DHW heating is expected to continue the rapid growth. In terms of energy management, a major advantage of electric water heaters (EWHs) over fossil fuel-based options is that EWHs can be effectively integrated into the overall building Demand Side Management (DSM), which has been shown to provide benefits such as peak load reduction (peak shaving), lower electricity costs, and integration of intermittent renewable energy resources. These DSMs can also incorporate or include flexible pricing structures and on-site generation with additional capabilities to predict conditions and store energy. Thermal energy stored in water storage tanks can decouple the demand for electricity and thermal power. There are already more than 50 million electric water heaters (EWHs) in the U.S., comprising about 50% of all water heaters in the country, which can provide a potential storage capacity of approximately 50 GWh [3]. With the built-in energy storage capability, EWHs have the potential to provide services such as maximizing self-consumption of on-site renewable electricity generation, peak load reduction (peak shaving), lowering electricity costs under dynamic or flexible pricing structures, and integrating intermittent renewable energy resources into the power systems. DHW provision systems are commonly designed so that more than enough hot water is always available to avert comfort violations and the corresponding penalties that may be incurred. Thus, these systems may experience significant energy loss without an accurate prediction of DHW usage. Moreover, a reliable prediction of the DHW consumption profile over a control horizon is of paramount importance to obtaining the optimal performance. So far, most of the existing DSM studies concerning EWHs have been carried out based on artificially generated profiles with extensive statistical information [4–6]. The three yearly DHW demand profiles described by Jordan et al. [7] have been commonly used in these studies. Nevertheless, when it comes to different buildings in real-life settings, the demand behavior may vary significantly from one building to another and individual building behaviors may not necessarily converge to the desired distribution. Thus, a data-driven approach with data gathered on-site would be more reliable for predictions and further optimal control based on the predictions.

When it comes to predicting DHW consumption, different factors need to be taken into consideration. Region, culture, household size, and personal preferences are important contributing factors in the hot water usage profile of a household [8], affecting peaks during morning and evening, duration of use, and average consumption. As mentioned earlier, the average DHW usage was estimated at about 64 liters per person per day (LPD) for a U.S. household [2], while it was reported to be around 43 LPD and 33 LPD for Finish and Swedish households, respectively [9, 10]. Forecasting DHW can be targeted toward different sizes of households personal information may be required and data acquisition can be very privacy intrusive especially for individual users. The problem also becomes more of a human behavioral prediction problem [11]. While predicting the DHW consumption of a multi-family dwelling can be essentially treated as a time series forecasting problem [12]. The approaches that deal with single and multi-family usage can be very different and approaches developed can not be applied to or unable to generate satisfying results for both problems in general.

Different approaches can be found in the literature for predicting DHW consumption including an analytical bottom-up approach [8], a feature specified bottom-up approach [13], and a statistical approach with Autoregressive–Moving-Average (ARMA) [14, 15]. With the development of machine learning algorithms, data-driven techniques for forecasting DHW consumption are becoming more and more popular. Artificial Neural Network (ANN) [16], Recurrent Neural Network (RNN) [17], and Reinforcement Learning [18] among others have been implemented for DHW consumption predictions and demonstrated promising performance. Gelanzanskas and Gamage [19] compared various DHW usage forecasting models and concluded that seasonal decomposition of the time-series is of the utmost importance for obtaining accurate predictions.

In an EWH system scheduling problem, the main sources of uncertainty are associated with hot water consumption prediction, ambient temperature, and cold water supply temperature over the planning horizon. It is worth noting that all the reviewed prediction approaches have their corresponding uncertainty levels, which need to be considered when formulating an optimization problem. Hong et al. [20] formulated an optimization problem to obtain the optimal temperature scheduling for an air-conditioning system which could be inspirational for other energy systems. As there existed uncertainty in the price and temperature predictions, they utilized fuzzy parameters for formulating the optimization problem. Thanks to the advances in robust optimization and optimization under uncertainty, different theories and methodologies can be used to take uncertainties into account in an optimization problem including probability theory [21], evidence theory, possibility theory, Bayes theory, and imprecise probabilities [22]. The most appropriate methodology for a given application should be selected considering data availability, uncertainty level, and problem complexity. Even though statistical models [23] or machine learning techniques [24] have proven their capabilities to model or quantify uncertainties, they have been rarely used water heating systems to develop stochastic or robust formulations for predictive control problems.

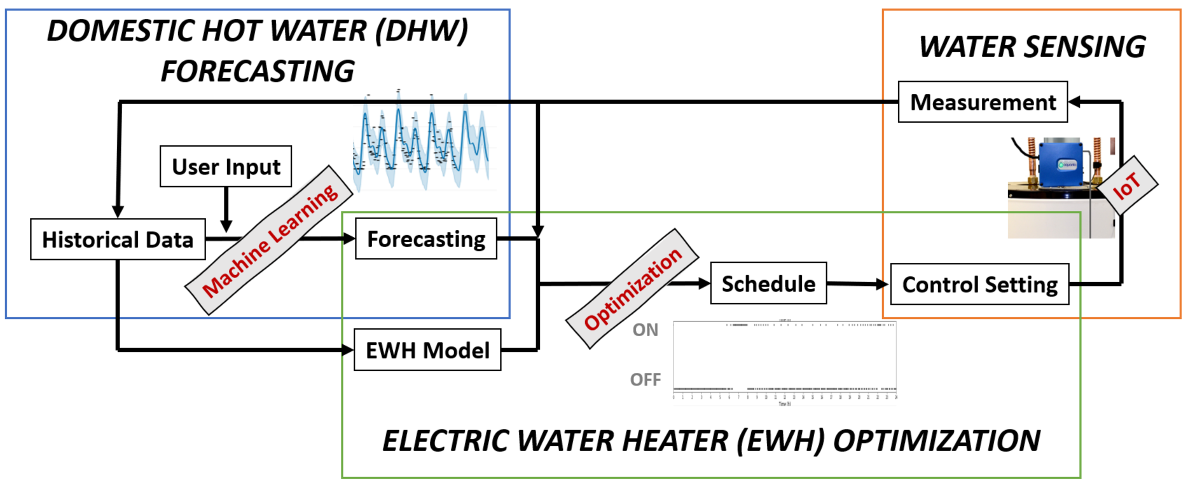


Figure 1: System design of the Electric Water Heater Smart Scheduling and Control System which consists of the Water Sensing that measures and stores data using Internet of Things (IoT) hardware and smart sensors, the DHW Forecasting that generates forecasting of hot water usage with machine learning algorithms from historical data, and the EWH Optimization that produces optimal schedules and controls for the EWH.

In an attempt to bridge the above-mentioned gap, this paper introduces a data-driven, predictive control scheme for optimizing the performance of an EWH system with the uncertainties taken into account. Unlike previous studies, real-life historical data has been used to formulate the robust optimization problem. The designed system, illustrated in Figure 1, consists of three main components named Water Sensing, DHW Forecasting, and EWH Optimization. The data obtained from the water metering is used to generate a forecast of the next day's DHW consumption profile. Combined with an EWH model, Model Predictive Control (MPC) simulations are performed to provide optimal control signals. Uncertainties in the DHW demand prediction are considered by specifying upper and lower bounds to ensure a robust control that brings financial savings for the consumer while maintaining thermal comfort. The performance of the system has also been investigated when participating in a demand response (DR) program. With all these features, the proposed system, referred to as Electric Water Heater Smart Scheduling and Control, has the potential to be integrated into real-world energy management systems to achieve the benefits of more intelligent control of electric water heating. While this paper focuses on the software and algorithm side of the whole designed system, the designed IoT smart water meter which has the capability to measure water usage noninvasively is beyond the scope of this paper.

The rest of the paper is organized as follows. Section 2 outlines the methods and techniques employed for the proposed system. Section 3 presents and discusses the results obtained from the MPC simulations. Finally, Section 4 concludes the paper and provides recommendations for future work.

2. Methodology

The optimization problem formulated serves to achieve two main functions. First, it enables an optimized expected schedule for the next day EWH operation. It allows building operators and users to visualize the following day's operation and identify potential problems that might happen during some of the critical hours. Second, it is constantly resolved during the day to adjust and output the optimal control decisions. This allows the understanding of the current status of the system and future decisions based on what happened. It also allows the EWH to respond to various Demand Response programs or other emergency calls while still keeping the operation schedule close to optimal by minimizing cost and maintaining user comfort.

2.1. Control Model and Variables

With data and controls recorded and implemented every 5 minutes, the 24 hours of the planning horizon can be visualized in Figure 2. The system will solve for the optimized schedule of EWH over the whole remaining planning horizon with the initial conditions that are updated at each time step. Further, the nearest time step will take the action from the optimal schedule generated. The states of the EWH are calculated with an efficient EWH model in combination with data-driven predictions that will both be discussed in the following paragraphs.

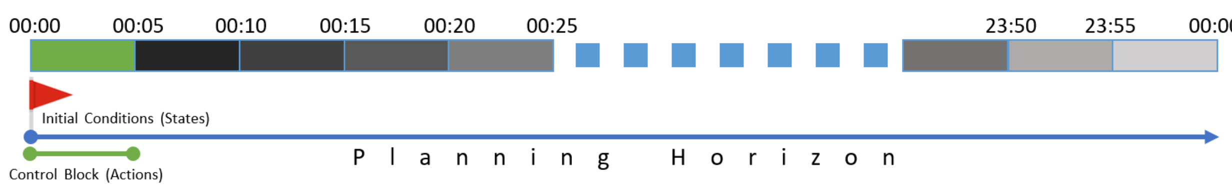


Figure 2: Planning horizon visualization with a day divided into 288 five minute intervals where flag represents the initial conditions.

2.2. Electric Water Heater Model

For the purpose of this paper, a fully mixed single-node EWH model is chosen since it is most computationally efficient and provides a reasonable confidence in making control decisions for EWHs. A Single-Node EWH model still is precise when the EWH is turned on for heating while precision drops when EWH is discharging water [25, 26]. Many existing works of control EWH systems using a Single-Node model [27, 28] showed promising results. Admittedly, DHW use in terms of water flow might be affected by the differences in DHW temperature: a higher DHW setpoint might lead to reduced flow and volume usage with more cold water mixed. A better way of quantifying DHW use could be in terms of energy(enthalpy). Nevertheless, due to the limitation that the dataset does not gather DHW temperature data, volume usage is used for the prediction and modeling of EWH heat balances. The heat loss from the water mass to the ambient environment (W) can be modeled as:

$$\dot{Q}_{\text{loss}} = A(1/R)(T_{\text{h}} - T_{\text{a}}) \tag{1}$$

where A is the surface area of the water heater, R is the thermal resistance of the tank insulation, T_{h} is the hot water temperature inside the tank, T_{a} is the ambient temperature. In addition, the heat loss due to the demand for hot water can be modeled as:

$$\dot{Q}_{\mathrm{demand}} = \dot{M}_{\mathrm{w}} c_{\mathrm{p}} (T_{\mathrm{h}} - T_{\mathrm{in}}) * 1000 \tag{2}$$

Where $\dot{M}_{\mathrm{w}}$ is the average hot water demand rate during the time interval, c_{p} is the isobaric specific heat capacity of water in , and T_{in} is the supply domestic cold water temperature. Lastly, the heat supplied from the EWH can be modeled as:

$$\dot{Q}_{\mathrm{gen}} = P \eta S \tag{3}$$

where P is the power consumption, η is the efficiency of the electricity-to-heat transformation, S is the binary variable representing the on/off state of the water heater. The heat balance equation then can be derived as follows:

$$M c_{\mathrm{p}} \frac{dT_{\mathrm{h}}}{dt} = -\dot{Q}_{\mathrm{loss}} - \dot{Q}_{\mathrm{demand}} + \dot{Q}_{\mathrm{gen}} \tag{4}$$

where M_{w} is the total mass of water stored in the water heater. An approximate solution can be obtained by taking the discrete average behavior over the 5 minute time interval of each control block to formulate a mixed integer linear programming problem. The governing equation for heat balance thus becomes:

$$\begin{aligned} (T_{\mathrm{h},i+1} - T_{\mathrm{h},i}) * M * c_{\mathrm{p}} / \Delta\, t = -A(1/R)(T_{\mathrm{h},i} - T_{\mathrm{a}}) - \\ \dot{M}_{\mathrm{w},i} c_{\mathrm{p}} (T_{\mathrm{h},i} - T_{\mathrm{in}}) * 1000 + P \eta S_i \end{aligned} \tag{5}$$

The parameters used specifically in solving the governing equation are shown in Table 1. The specific parameters of the EWH can be set by referring to manufacturer documents or determining experimentally through data collection. In real-world settings, a data driven EWH would be desired since it would precisely fit each EWH in different conditions. The EWH used in this paper is a 950 liter PVI Durawatt [29] commercial scale electric water heater. It is an EWH widely used in many multi-unit apartments with shared DHW supply. Electricity prices C_{on} and C_{off} are referenced from ConEd [30]. Further, the upper and lower limits of the DHW temperatures are set to avoid extreme high temperatures that could shorten the lifespan of components, preventing Legionnaires' disease, and complying local laws [31, 32].

2.3. Objectives and Settings

The objectives for many energy systems can vary from minimizing energy consumption, peak demand, or cost to maximizing user comfort or stability or a mix of both. For a EWH smart scheduling and control system addressed in this paper shown in Figure 1, it is important to have capabilities to adjust accordingly based on different types DSM. To show the capability of the system, two examples from Price-Based Program (PBP) and Incentive-Based Program (IBP) are chosen. From PBP, a Time of Use (ToU) tariff is chosen to be the objective for the problem to minimize the cost. Depending on the specific program chosen, ToU tariffs and demand charge may be considered. Thus, for a system modeled in this problem which only switches on and off with a constant power input, it is more reasonable to focus on the kWh cost. The chosen program for this paper is based on Consolidated Edison (ConEd) [30] PSC10-Class No.1 Rate II tariff shown in Figure 3.

Table 1: Parameters chosen in the optimization problem

Symbol	Meaning	Value
A	**surface area,** m^2	6
R	**thermal resistance,** $(m^2K)/W$	1
$c_\mathbf{p}$	**isobaric specific heat of water,** $kJ/(kgK)$	4.18
P	**nominal power of EWH,** W	50000
η	**efficiency of the EWH**	0.95
M	**mass of water in EWH,** kg	946
$T_\mathbf{in}$	**input cold water temp,** C	17
$T_\mathbf{a}$	**ambient temperature,** C	17
$C_\mathbf{on}$	**on peak price (summer months),** $\$/kWh$	0.345
$C_\mathbf{on}$	**on peak price (other months),** $\$/kWh$	0.125
$C_\mathbf{off}$	**off peak price,** $\$/kWh$	0.0132
$T_\mathbf{up}$	**upper limit of DHW temp,** C	72
$T_\mathbf{low}$	**lower limit of DHW temp,** C	49
$T_\mathbf{ini}$	**initial temperature of DHW,** C	52
$\Delta\, t$	**control time interval,** s	300

Regarding IBP, these programs normally require a coordinated reduction in energy use for all energy systems at demand side. While EWH alone plays a part of the overall electricity consumption for buildings, this smart scheduling and control system can be optimized and controlled to contribute to the overall reduction for the whole building. A high penalty can be added to the objective function during the DR period to motivate the EWH to be planned off and use its storage capacity to shift its load in advance. Once the DR call is received, normally with a minimal notice period of 1 to 2 hours, the MPC can take in that information and modify the objective for the following EWH operation schedule.

The target multi-unit building chosen has about 130 residents in 60 units. The building has two PVI Durawatt electric water heaters with specifications described in Table 1. One EWH is the main one running with the other one as a backup. The EWH is also located in the basement with a stable room temperature. To generate the DHW use profile, we aggregate the data from 77 individual EWHs given in [33]. This aggregated profile gives an example DHW usage behavior for a large population of residents that can be used to mimic a multi-family apartment building

2.4. Hot Water Demand Forecasting

The dataset used for this paper is reported in Refs. [33, 34]. The data is gathered from 77 electric water heaters over 120 days in South Africa. The days recorded are divided into four seasons with 30 days for each season in the months of February, March, July, and September. Since South Africa is in the Southern Hemisphere, the coolest months are July and August while the warmest months are around January and February. The average temperature does not show a large variation over a typical year with lows around $45°F$ to highs around $61°F$. Data include both water use, ambient temperature, and power for each electric water heater at a frequency of 1 minute. This dataset is chosen because it gathers data for a large number of EWHs over an extended period of time, providing opportunities to compare both individual and aggregate behaviors. The dataset does provide multiple measurements for potential feature correlation analysis to understand how other factors might affect DHW usage, but the limited features provided motivate the forecasting to be

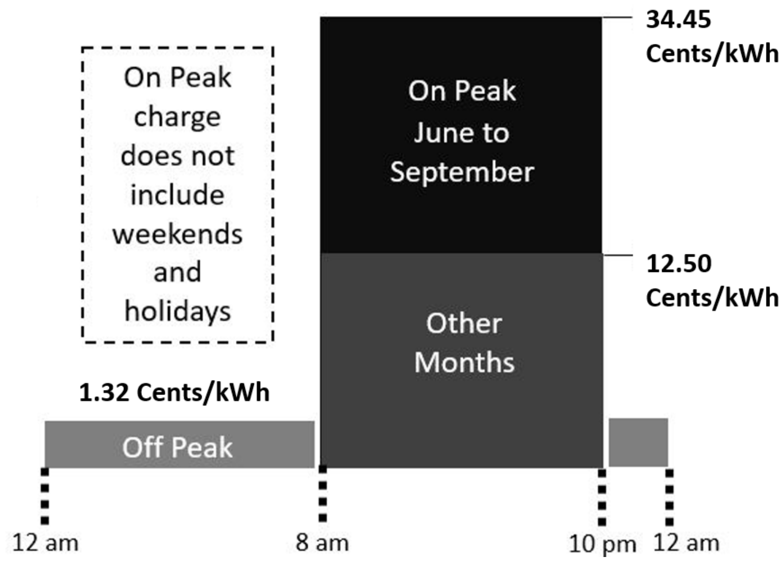


Figure 3: Consolidated Edison (ConEd) SC10-Class NO.1 Rate II Time of Use (ToU) tariff which is used to quantify electricity cost in this study.

a pure time series forecasting.

PROPHET [23] is employed for this DWH usage prediction problem. PROPHET is an open source software developed by Facebook that deals with common time series problems. Similar to ideas discussed by Gelanzanskas [19], PROPHET treats time series forecasting as a curve-fitting problem with the summation of multiple levels of curves:

$$y(t) = g(t) + s(t) + h(t) + \epsilon_t \tag{6}$$

Where the overall trend $g(t)$ is combined with seasonalities $s(t)$ from yearly, weekly, and daily levels in addition to the holiday effects $h(t)$ as well as noises ϵ_t extra conditional seasonality and regressor specified. Specifically, the model trend can be either a saturation growth model:

$$g(t) = \frac{C(t)}{1 + \exp(-k(t-m))} \tag{7}$$

or a piecewise linear model:

$$g(t) = (k + a(t)^T\delta)t + (m + a(t)^T\gamma) \tag{8}$$

depending on the training data with $C(t)$ being the time varying carrying capacity, k being the growth rate, and m being an offset parameter. To determine the change points in the trend, the rate of change is estimated with Maximum Likelihood Estimation (MLE) with a prior defined as a Laplace distribution. With a default value of 0.05, increasing the diversity parameter of the Laplace distribution can make the trend more flexible. Seasonalities are fitted using Fourier Series for the period effects with a stack of sine curves and a number of parameters that need to be estimated depending on the order of Fourier Series chosen:

$$s(t) = \sum_{n=1}^{N} a_n \cos(\frac{2\pi nt}{P}) + b_n \sin(\frac{2\pi nt}{P}) \tag{9}$$

Where n is the order of Fourier Series chosen and a_n and b_n are the parameters that need to be estimated. In this case, $P = 365.25$ is the interval length defined in Fourier Series for the yearly trend, and $P = 7$ is the interval length for the weekly trend. Holiday effects $h(t)$ are predefined with a list of U.S. holidays but can also be additionally specified. PROPHET also captures and predicts the uncertainty in both the overall trend, seasonalities, and additional observation noises. For uncertainty in the overall trend, it is assumed that the future change would replicate a similar rate as previously detected. By default, PROPHET samples 1000 points and sets an uncertainty interval of 80%. While for the uncertainty in seasonality, a generative model with full Bayesian Sampling using Monte Carlo Markov Chain technique can be defined to generate the uncertainty interval. This technique can be suitable for this problem to predict the aggregate behavior of 77 EWHs to mimic a multi-family dwelling.

2.5. Optimization and Robust MPC Formulation

First to generate the optimal schedule through the planning horizon, an integer program assuming deterministic prediction can be formulated as below:

$$\begin{aligned} \min \quad & \sum_{i=1}^{N} C_i * P * S_i \\ \text{s.t.} \quad & C_i = \begin{cases} C_{\text{on}} & \text{if during on-peak hours} \\ C_{\text{off}} & \text{if during off-peak hours} \end{cases} \\ & T_{\text{low}} <= T_{\text{h},i} <= T_{\text{up}} \\ & (T_{\text{h},i} - T_{\text{h},i-1}) * M * c_{\text{p}} / \Delta\, t = -A(1/R)(T_{\text{h},i-1} - T_{\text{a}}) - \\ & \dot{M}_{\text{w},i} c_{\text{p}} (T_{\text{h},i-1} - T_{\text{in}}) * 1000 + P\eta S_i \\ & T_{\text{h},0} = T_{\text{ini}} \end{aligned} \tag{10}$$

Where the objective is to minimize electricity cost based on sample ToU tariff while making sure the temperature of the hot water is maintained between the limits and the heat balance of the hot water heater is satisfied. This basic formulation assumes a deterministic expected DHW demand in the future. Solving this optimization allows the visualization and understanding of the expected EWH behavior and electricity cost for the upcoming day.

To account for uncertainties from DHW forecasting, at each future time step, a range of the probable DHW consumption rates is calculated by PROPHET. The effects of a higher than predicted DHW consumption would lead to a greater value of heat loss, causing a lower than expected value of the DHW temperature inside the tank. On the other hand, a lower than expected DHW consumption would cause a higher than expected DHW temperature. Thus, when producing control outputs during the MPC simulations, it is important to make sure that the system is robust through these possible variations of future DHW consumption values at the upcoming time step. Based on this relationship, the uncertain DHW consumption can be modelled by modifying the temperature constraints in the optimization as follows,

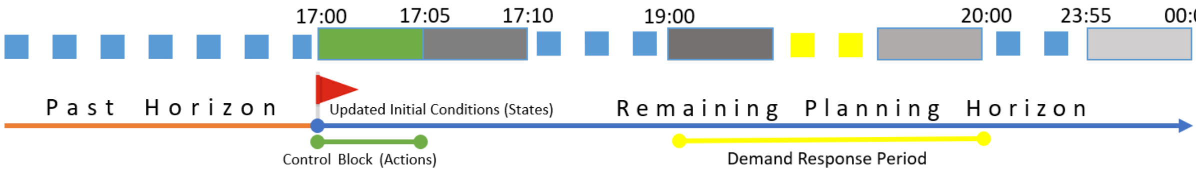


Figure 4: Planning horizon visualization with a DR notification received at 5pm for demand response period during 7pm to 8pm.

$$
\begin{aligned}
\min \quad & \sum_{i=1}^{N} C_i * P * S_i \\
\text{s.t.} \quad & C_i = \begin{cases} C_{\text{on}} & \text{if during on-peak hours} \\ C_{\text{off}} & \text{if during off-peak hours} \end{cases} \\
& T_{\text{h},i} - ((\dot{M}_{\text{w up},i-1} - \dot{M}_{\text{w},i-1}) * c_{\text{p}} * (T_{h,i-1} - T_{in}) * \Delta\, t)/(M * c_{\text{p}}) >= T_{\text{low}} \\
& T_{\text{h},i} + ((\dot{M}_{\text{w},i-1} - \dot{M}_{\text{w low},i-1})) * c_{\text{p}} * (T_{h,i-1} - T_{in}) * \Delta\, t)/(M * c_{\text{p}}) <= T_{\text{up}} \\
& (T_{\text{h},i} - T_{\text{h},i-1}) * M * c_{\text{p}}/\Delta\, t = -A(1/R)(T_{\text{h},i} - T_{\text{a}}) - \\
& \dot{M}_{\text{w},i} c_{\text{p}} (T_{\text{h},i-1} - T_{\text{in}}) * 1000 + P\eta S_i \\
& T_{\text{h},0} = T_{\text{ini}}
\end{aligned}
\tag{11}
$$

As time propagates during the simulation, the initial temperature T_{ini} is updated from the EWH model while in real-life application, a temperature sensor is assumed to provide reliable feedback on the updated temperature.

Distribution Load Relief Program (DLRP) is an example of an emergence demand response program by ConEd. The program has a 2 hour notification period. An example of this program which notifies at 5pm for demand reduction during 7pm to 8pm is visualized in Figure 4. The objective function for the optimization is modified to add a penalty, acting like the potential incentive, for turning on the EWH during the DR period. Doing so would demotivate the EWH from turning on during this period of time and thus reduces both the average power and overall electricity consumption without jeopardizing thermal comfort. As a result, the robust optimization formulation is modified as follows,

$$
\begin{aligned}
\min \quad & \sum_{i=1}^{N} C_i * P * S_i + \sum_{j \in DR\, period} Pe_j * P * S_i \\
\text{s.t.} \quad & C_i = \begin{cases} C_{\text{on}} & \text{if during on-peak hours} \\ C_{\text{off}} & \text{if during off-peak hours} \end{cases} \\
& T_{\text{h},i} - ((\dot{M}_{\text{w up},i-1} - \dot{M}_{\text{w},i-1}) * c_{\text{p}} * (T_{\text{h},i-1} - T_{\text{in}}) * \Delta\, t)/(M * c_{\text{p}}) >= T_{\text{low}} \\
& T_{\text{h},i} + ((\dot{M}_{\text{w},i-1} - \dot{M}_{\text{w low},i-1})) * c_{\text{p}} * (T_{\text{h},i-1} - T_{\text{in}}) * \Delta\, t)/(M * c_{\text{p}}) <= T_{\text{up}} \\
& (T_{\text{h},i} - T_{\text{h},i-1}) * M * c_{\text{p}}/\Delta\, t = -A(1/R)(T_{\text{h},i-1} - T_{\text{a}}) - \\
& \dot{M}_{\text{w},i} c_{\text{p}} (T_{\text{h},i-1} - T_{\text{in}}) * 1000 + P\eta S_i \\
& T_{\text{h},0} = T_{\text{in}}
\end{aligned}
\tag{12}
$$

In addition to the capability to optimize control schedules for the ToU tariff structure and respond to DR programs, the system can also incorporate other price structures and energy sources such as critical peak pricing and onsite solar generation. For example, dynamic pricing requires the predictions of the electricity prices that can be accomplished with the similar methodology using PROPHET and adding another uncertainty variable into the robust MPC formulations.

2.6. Performance Evaluation

To evaluate the performance of the control strategies, we quantify and compare two of the most important factors for a demand-side user: electricity cost and user comfort. The cost can be calculated by the actual schedule of EWH through the simulations and compared to a baseline situations. In this paper, the baseline is constructed based on a thermostatic control, namely a simple and widely used rule-based temperature control method which maintains the temperature within the upper and lower limits. Evaluating the performance of the system with regard to thermal comfort needs further analysis. In some states in the US such as New York, it is required for residential buildings to provide DHW with a minimum temperature of $120°F$ always. Building management companies could be subject to significant fines and penalties starting from $250 per day [32]. Nevertheless, the rules normally get relaxed as a minor deficiency in temperature for a short period of time is typically tolerable. Thus, to evaluate the performance, a 95% fulfillment limit is set. If DHW temperature is maintained above $120°F$ for over 95% of the time during the day, the following minor penalty would be applied based on the average temperature violation and the duration of violation with unit penalties of Pe_1 and Pe_2:

$$Pe_{\text{vio}} = Pe_1 * \overline{T_{\text{vio}}} + Pe_2 * t_{\text{vio}} \tag{13}$$

where T_{vio} is the temperature of violation and t_{vio} is the duration of violation. If the fulfillment time drops below 95%, it would be considered a major violation which is not tolerable and would incur the large penalties.

For DR program in New York State specifically, there exists a large variety of criteria designed and enforced by wholesale power system operators and energy suppliers like New York Independent System Operator (NYISO) and ConEd. To calculate the demand reduction for a DR program, the normal procedure is to calculate the Customer Base Load based on recorded usage from previous days with adjustments [35, 36]. Thus, to evaluate how well the EWH responds to the overall building demand reduction call, the average base load is calculated by generating the anticipated schedules over past days and then compared to the actual load during the day with a DR call.

3. Results and Discussion

3.1. Domestic Hot Water Forecasting

3.1.1. Dataset Analysis and Visualization

Considering DHW usage over 30 days for one EWH from the dataset, a recognizable pattern can be observed for individual DHW usage with a larger peak with shorter duration in the morning and a lower peak with longer duration in the evening. While the duration of DHW use is similar in different seasons, the average daily DHW use takes a higher value in winter and a lower value in summer. Specifically, winter has the highest average daily DHW use of 23.8 L, following by spring of 20.9 L, fall of 17.2 L, and summer of 16.8 L. This proves seasonal variation of household's DHW use with 41.7 % increase from warmer months to cooler months.

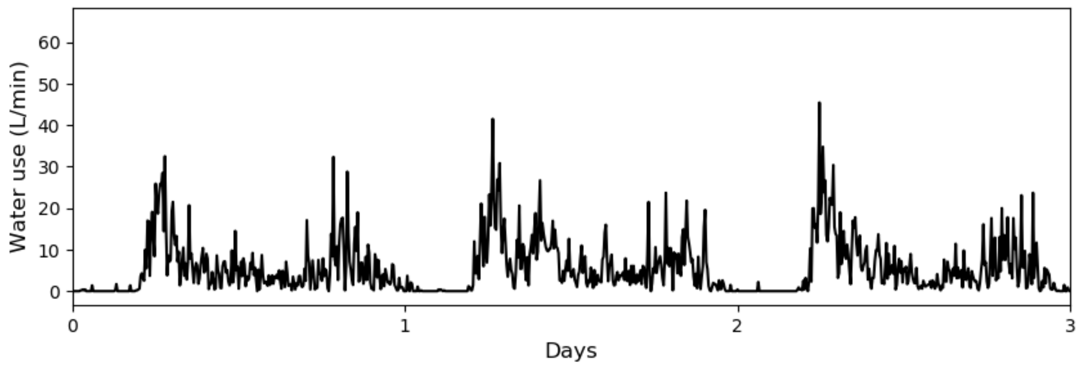


Figure 5: Aggregated pattern of 77 EWHs for three example days.

A correlation analysis of the dataset shows that DHW use is relatively independent of outdoor air temperature, with a correlation coefficient of 0.004. This is mainly because the dataset is provided with one month for each season preventing year-long training data to show the continuous seasonal variations. With one month of data used for each season, in addition to the well-maintained indoor temperature, the correlation is thus low and neglectable on a sub-hourly basis. The seasonal variation can be better understood when comparing the daily usage versus the daily average temperature. These two variables show a moderate correlation of 0.23. Further, the average seasonal usage numbers are much more convincing on proving the seasonal variations discussed in the following paragraph. Thus, ambient temperature is not included in the DHW forecasting model which aims to predict sub-hourly usage of DHW, leading to a pure time-series treatment of the DHW forecasting with this dataset.

In order to use the data to mimic a multi-dwelling apartment complex, the data from the 77 individual EWHs is aggregated as shown in Figure 5 for 3 typical days in the summer season. The aggregated data also shows a more recognizable daily pattern for multi-family dwellings [37]. The aggregated data shows the daily average usages for different seasons to be 7670.9 L for summer, 7821.6 L for fall, 10850.1 L for winter, and 9522.97 L for spring, leading to a daily average use of 8966.4 L over the year. Comparing to the 130 resident target building in the U.S. with 64 liters per day per person usage, the dataset can well represent the usage in the target building with a discrepancy less than 10%. Thus, the aggregated profile will be used for training and testing the model.

3.1.2. Forecast Generations

The forecasts were generated using PROPHET and are shown in Figure 6. The black dots represent the training data while the grey line represents the fitted curve and the predicted values of the following day and the grey shades represent the uncertainty range. Ideally in real-world settings, over a year of data would be desired to capture more patterns. The package generates multiple plots for visualization in Figure 7. It shows how PROPHET's additive model works by adding up (a) the overall model trend defined as a piecewise linear model, (b) the daily and (c) the weekly seasonalities fitted with Fourier Series curves, and (d) the extra morning and evening regressors. When predicting demand at one timestamp into the future, the trend is assumed to be maintained with possible changepoints sampled randomly. In addition to the time of day value, day of week, and morning and evening regressor values summed. From Figure 7, the training data shows the most obvious pattern for the daily seasonality with the morning and evening peaks. If more data were gathered in the future, the seasonal behavior change of DHW demand and better

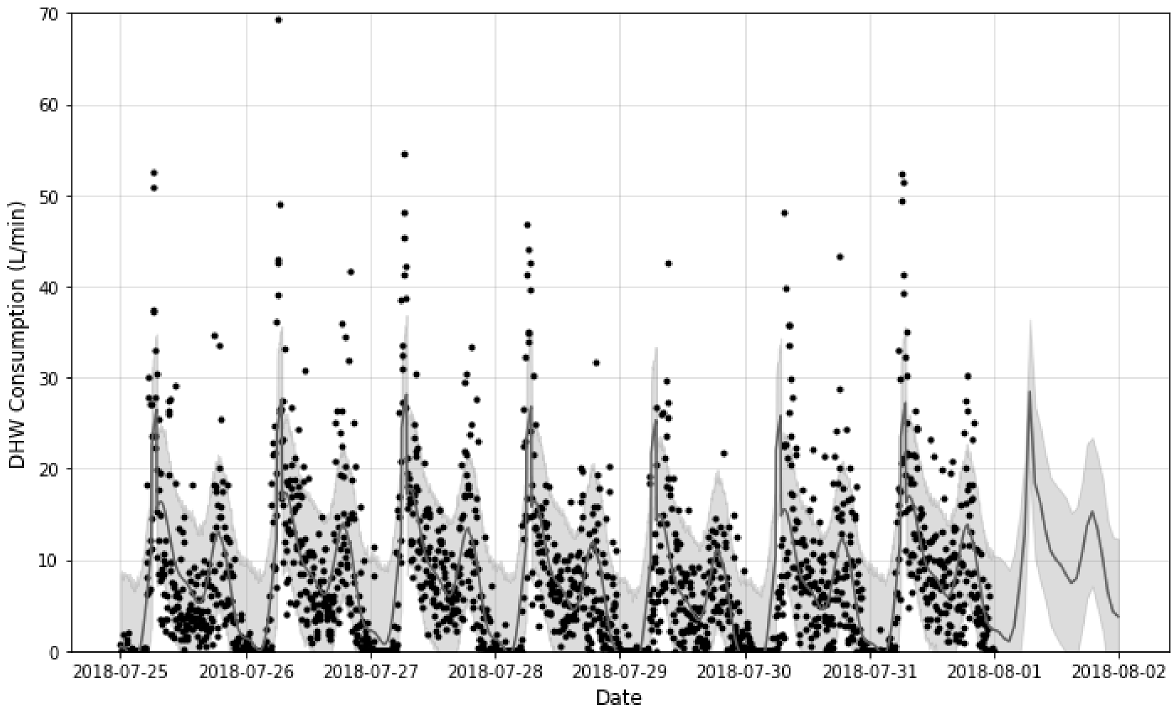


Figure 6: PROPHET prediction visualization.

weekly seasonalities can be expected. Further, with the incorporation of the morning and evening regressors, the "outlier" points that are filtered out by the daily seasonality curve got preserved to provide better predictions.

The forecasting result of a test summer day is shown in Figure 8 together with the actual DHW profile, and the upper and lower limits. It can be observed that the overall trend of the DHW profile is well captured and the fluctuation of the actual DHW consumption can be well covered within the upper and lower limits of the prediction while a few peaks are not fully covered. Note that, the seasonality profiles based on Fourier Series tend to smooth out the high morning and evening peaks and consider them as outliers. To better predict and incorporate these values into the possible range, additional regressors are added during the morning and evening peak times. The addition of the extra regressor significantly helps with producing an uncertainty interval that covers the variations in the actual values. Changing the uncertainty interval does impact the width of the upper and lower limits due to the sampling method that PROPHET uses. A proper uncertainty interval should maintain the robustness of the system while not affecting energy and cost savings. These results provide a good foundation for the following optimization of the EWH control schedules and model predictive control simulations. PROPHET's Python API also makes integration seamlessly with further data manipulation as well as optimization.

3.2. Electric Water Heater Optimal MPC Simulation

Optimizing the schedule for the EWH with a Mixed-Integer Programming formulation is a NP-Complete problem that requires extensive computing resources and time to get an optimal solution. A one day ahead optimal schedule can be generated by solving the optimization problem once. Furthermore, by solving the optimization repeatedly over the receding horizon, the optimal controls can be generated. Though global optimum is not guaranteed by the solution presented since the optimality gap does not necessarily converge to zero, only the first control signal is applied to the

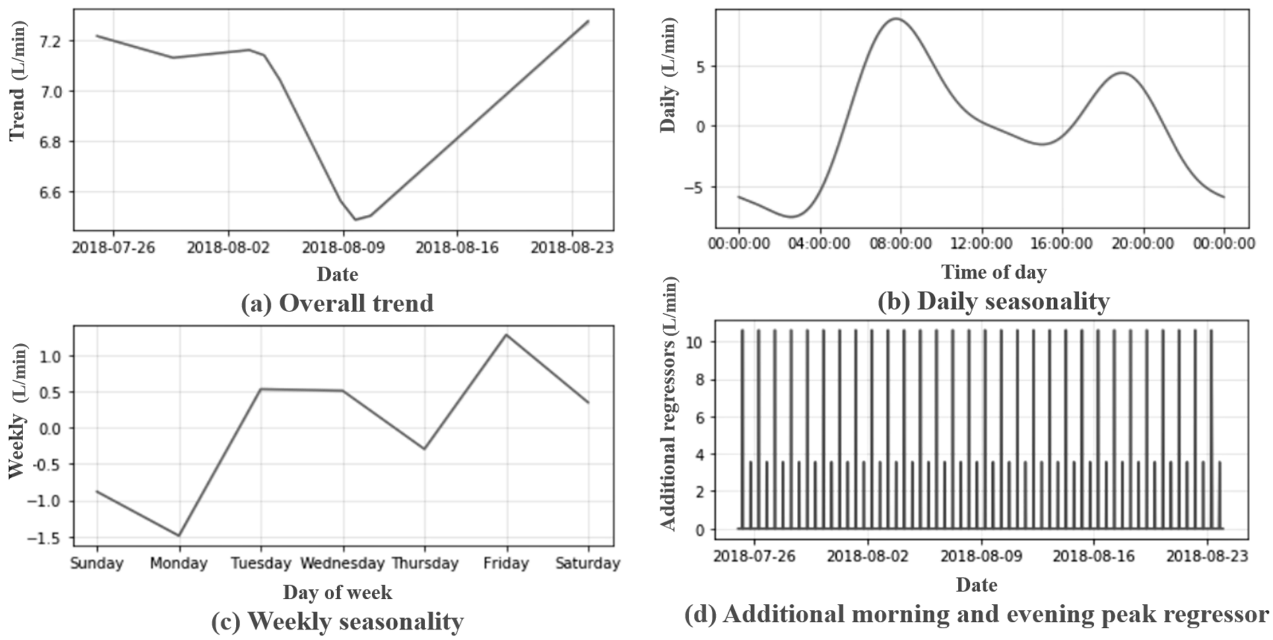


Figure 7: (a) Overall trend, (b) daily seasonality, (c) weekly seasonality, and (d) additional morning and evening peak regressors for the additive model that generates the resulted forecast.

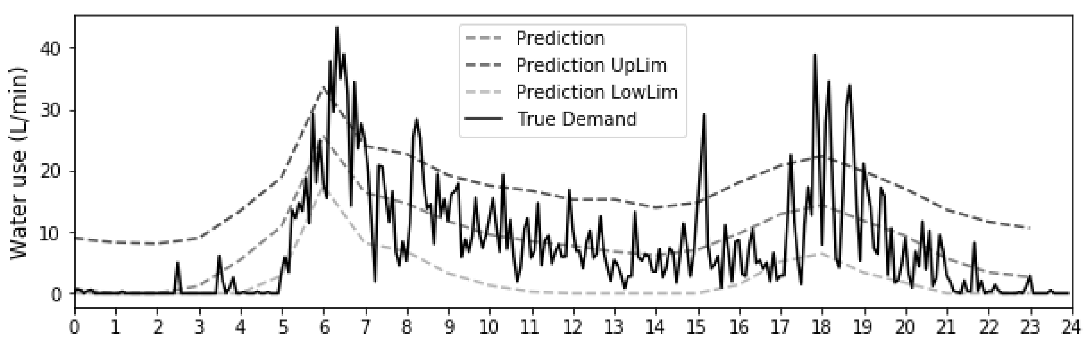


Figure 8: PROPHET prediction for one summer day.

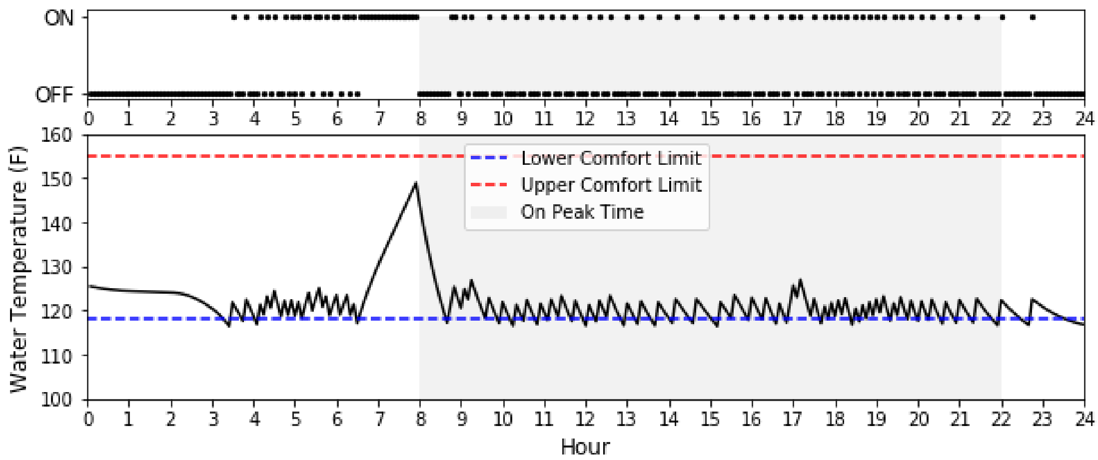


Figure 9: Optimal schedule of the EWH state and DHW temperature for one summer test day.

system. The continuously running MPC will repeatedly take in new information about the latest state of the system and generate a new optimal schedule for the remaining period of time.

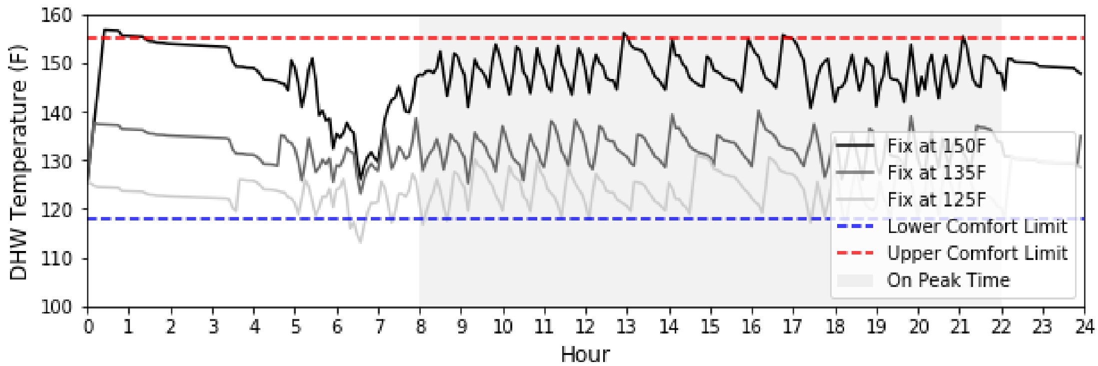
3.2.1. ToU (PBP) simulation and Performance

Using the predictions generated, Figure 9 shows the optimized schedule with the predicted hot water demand as a single deterministic value at each time step. The optimized schedule is minimizing the electricity cost based on the ToU tariff structure chosen with a higher electricity price from 8am to 10pm. The top subplot shows the on/off state of the EWH while the bottom subplot shows the anticipated DHW temperature inside the EWH. Repeating the process for optimizing a winter day, the expected electricity costs are \$68.06 and \$38.76 respectively.

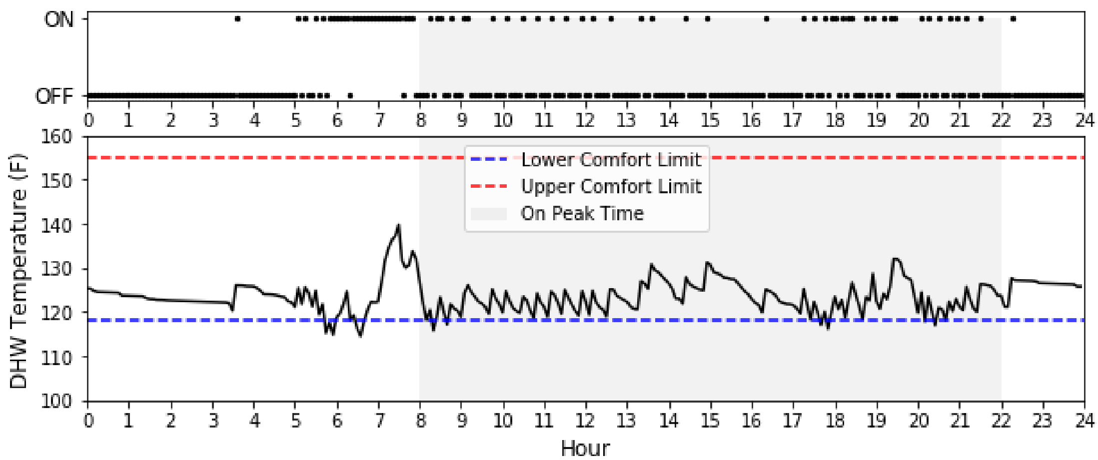
Observing the results from the optimal day ahead schedules, a period of preheating the water before 8am can be seen. The water temperature is raised to around $60°C$ $(140°F)$ which is much higher than the desired DHW temperature normally set at $49°C$ $(120°F)$. In this case, because the objective is set to minimize electricity cost under a ToU tariff, the behavior of preheating happens right before when electricity price increases drastically. This allows heat energy to be generated at a lower cost and be stored for future demand. Afterward, during the on-peak period, the main behavior of the EWH is to remain close to the lower bound of water temperature of $49°C$ $(120°F)$ in order to minimize the electricity cost. The expected electricity cost can be calculated and shown at the beginning of the day as a reference. Solving this optimization problem also outputs the next control action of the EWH as one step of the MPC simulation. By solving the optimization problem repeatedly as new measurements are feedback to the system, the system is able to determine the following control actions.

Conventional thermostatic control, an example of heuristic or rule-based control, tries to maintain a constant temperature set-point of DHW with a small range of variation. The system is controlled in response to demand: turn on the EWH if the lower limit temperature is reached, turn off EWH if the upper limit temperature is reached. One of the easiest Demand Side Management for households is actually to lower the DHW temperature set point. While Lowering DHW temperature can save a significant amount of energy, risk of being unable to meet the demand increases which could affect user comfort and cause high penalties.

Shown in Figure 10a are the expected behaviors of the EWH with DHW temperature set at



(a) Simulation for rule-based thermostatic control of EWH over one summer test day at different set-point temperature.



(b) Simulation for MPC of EWH state and DHW temperature over one summer test day.

Figure 10: Simulation for different control methods for EWH over one summer test day where (a) simulates the DHW temperature under rule-based thermostatic control and (b) simulates the EWH state and DHW temperature under MPC.

around 66$°C$ (150$°F$), 57$°C$ (135$°F$), and 52$°C$ (125$°F$) on the summer test day. Respectively, setting DHW at lower temperatures generates 17.0% and 29.1% savings in electricity cost compared to to a fixed set-point above 66$°C$ (150$°F$). Note that these control strategies are purely responsive to the previous time step's demand and have a high probability to run out of hot water if the EWH is not properly sized or a high demand is expected in the future. Thus, normally to avoid the violations, temperatures are set to a higher value. In both of the cases where DHW set points are 66$°C$ (150$°F$) and 57$°C$ (135$°F$), no violation occurs. While setting the temperature at 52$°C$ (125$°F$), 15 minutes of average violation of 2$°F$ occurred, dropping the fulfillment range to 99.0%. Figure 10b shows how could an EWH behave with prediction and MPC. Similar to the previously shown day-ahead schedule, the MPC simulation shows a preheating before 8am to utilize the lower electricity charges. In addition, because MPC constantly takes in updated temperature values while re-optimizing, the violation time is reduced to only 5 minute with an average of 1$°C$ (1.8$°F$). Listed in Table 2, MPC method generates 33.2% savings over the base cost with conventional control by maintaining water at 66$°C$ (150$°F$).

Repeating the process for the winter test day, the results are plotted in Figure 11a and the electricity costs simulated are shown in Table 3. Compared to the base case of conventional control, the reductions in electricity cost are 16.3%, 28.2% and 28.0% respectively. Note that due to the

Table 2: Electricity costs and comfort fulfillment comparison for one summer day simulation with different control methods.

	Electricity Cost	**Reduction**	**Fulfillment**
Fixed @66$^{\circ}C$ **(150**$^{\circ}F$**)**	\$85.23		100%
Fixed @57$^{\circ}C$ **(135**$^{\circ}F$**)**	\$70.71	17.0%	100%
Fixed @52$^{\circ}C$ **(125**$^{\circ}F$**)**	\$60.44	29.1%	99.0%
MPC	\$59.00	33.2%	99.7%

Table 3: Electricity costs and comfort fulfillment comparison for one winter day simulation with different control methods.

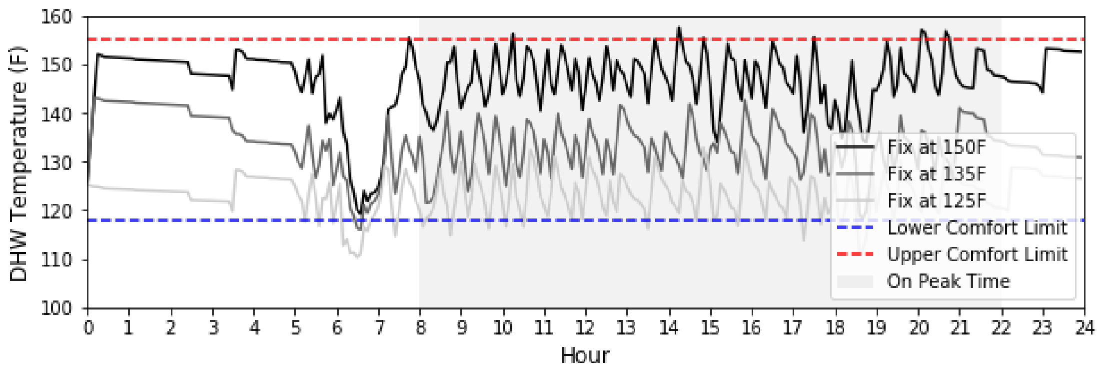
	Electricity Cost	**Reduction**	**Fulfillment**
Fixed @66$^{\circ}C$ **(150**$^{\circ}F$**)**	\$57.38		100%
Fixed @57$^{\circ}C$ **(135**$^{\circ}F$**)**	\$48.02	16.3%	99.0%
Fixed @52$^{\circ}C$ **(125**$^{\circ}F$**)**	\$41.22	28.2%	94.4%
MPC	\$41.35	28.0%	98.3%

higher DHW demand, the high morning peak causes the temperature to drop significantly below the set-points for conventional control methods if the temperature settings are too low. In this test example, if DHW temperature is set at around 49$^{\circ}C$ (120$^{\circ}F$), there would be 80 minutes of violation of average 2$^{\circ}C$ (4$^{\circ}F$) which makes the fulfillment rate drop below the 95% limit. Thus, it is expected to cause significant penalties and this control strategy is not desired. If MPC is used as the control method shown in Figure 11b, the violation time is significantly reduced due to the presence of DHW demand prediction while the electricity cost is still reduced by 28% compared to the baseline case. The result shows the capability of MPC to provide energy cost reduction and maintain user comfort when conventional controls are unable to achieve both objectives.

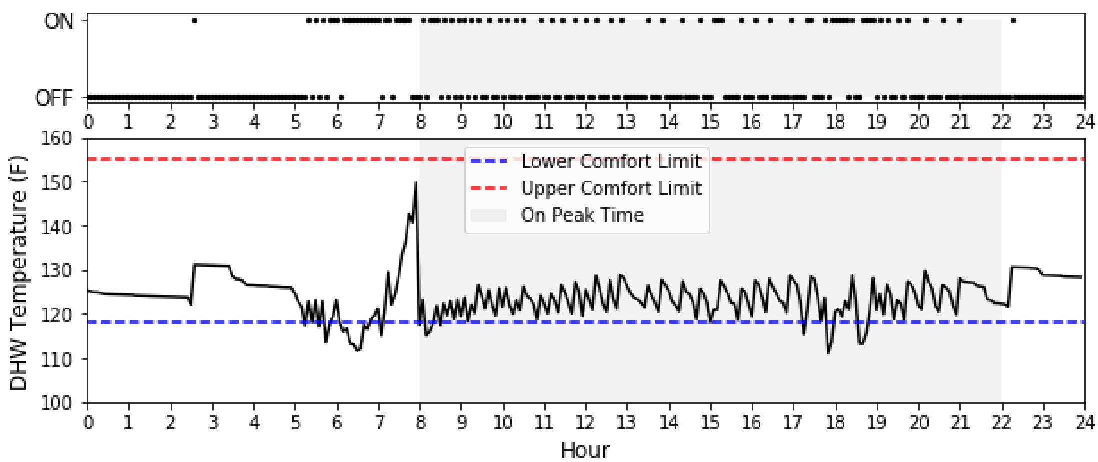
Performing an extended simulation over six test days, the results are shown in Figure 12. The baseline conventional controls with fixed DHW set-points are also plotted. The results for cost reduction and user comfort fulfillment are shown in Table 4. On average, 29.7% reduction in electricity cost and 98.9% user comfort fulfillment can be achieved. Consistently, MPC is reliable and efficient to reduce electricity cost and maintain user comfort.

Table 4: Electricity costs reduction and comfort fulfillment over six days of MPC simulation compared with rule-based thermostatic control simulation.

	Cost Reduction	**Fulfillment Improvement**	**Fulfillment**
Summer Day1	29.7%	1.8%	98.6%
Summer Day2	30.0%	2.9%	99.7%
Summer Day3	33.2%	0.7%	99.7%
Winter Day1	28.3%	2.5%	99.0%
Winter Day2	29.0%	2.2%	98.0%
Winter Day3	28.0%	3.9%	98.3%
Average	**29.7%**	**2.3%**	**98.9%**



(a) Simulation for rule-based thermostatic control of EWH over one winter test day at different set-point temperature.



(b) Simulation for MPC of EWH state and DHW temperature over one winter test day.

Figure 11: Simulation for different control methods for EWH over one winter test day where (a) simulates the DHW temperature under rule-based thermostatic control with a set point temperature at $66°C$ ($150°F$) and (b) simulates the EWH state and DHW temperature under MPC.

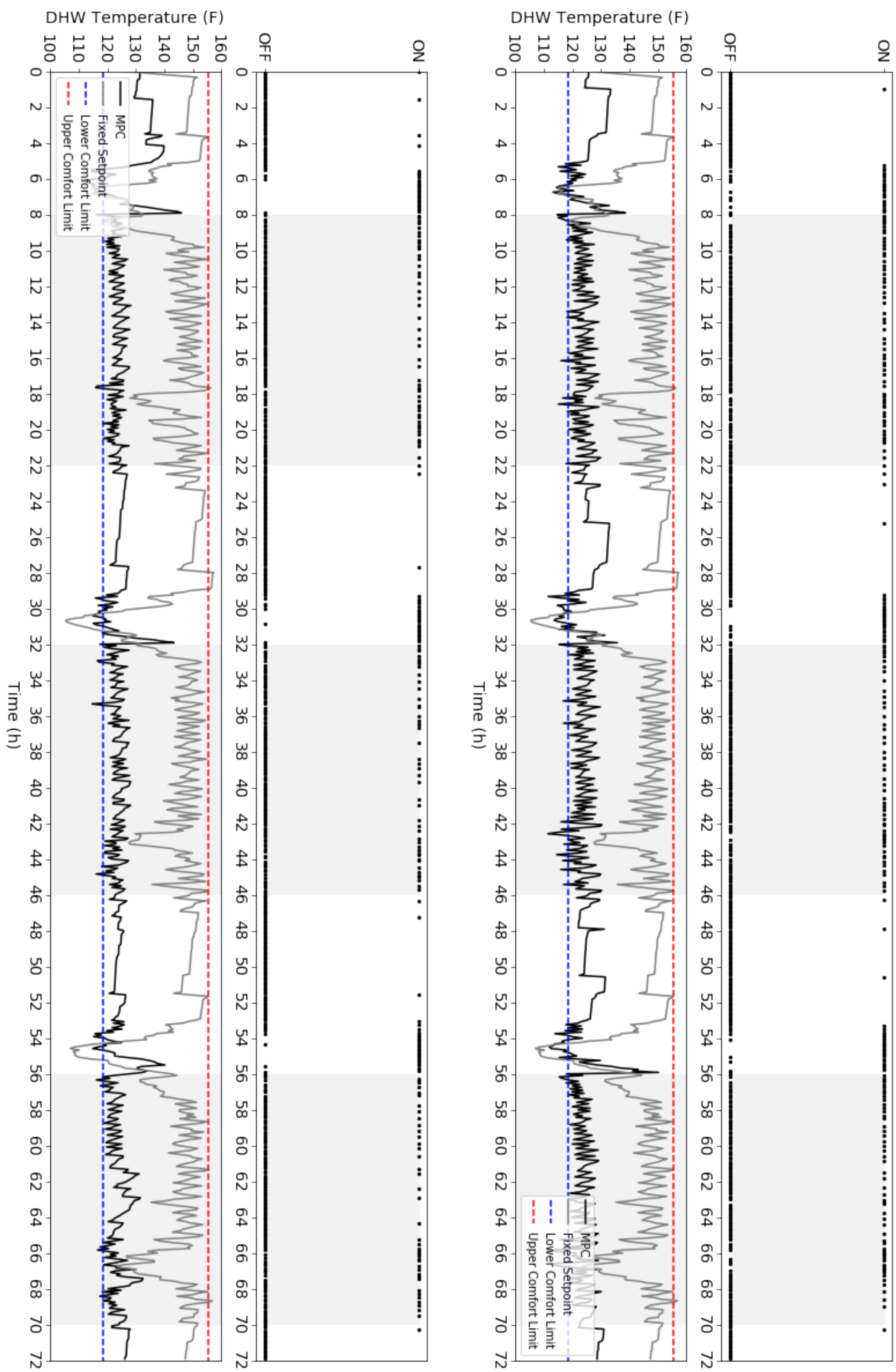


Figure 12: Left: Simulation of EWH state and DHW temperature over three summer test day using thermostatic control and MPC. Right: Simulation of EWH state and DHW temperature over three winter test day using thermostatic control and MPC.

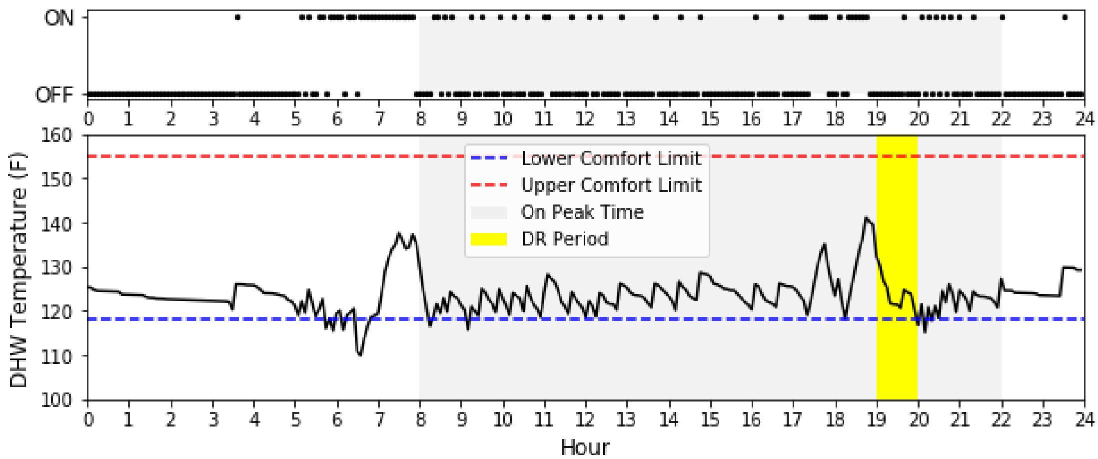


Figure 13: Adjusted schedule of EWH state and DHW temperature for demand response program notifying at 5pm and happening during 7pm to 8pm.

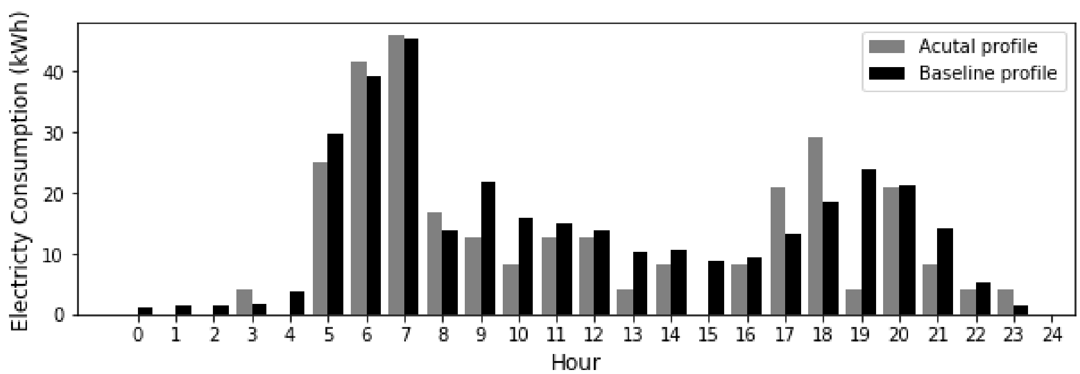


Figure 14: Comparison between the summer baseline load profile and the actual optimally adjusted load profile with demand reduction between 7pm to 8pm.

3.2.2. Demand Response(IBP) Simulation and Performance

Simulating a DR call made at 6pm for a demand reduction from 7pm to 8pm, the schedule will be instantly adjusted accordingly and the result is shown in Figure 13. With the modified objective, the EWH is planned to be off during this one hour period. Even though raising DHW temperature during the on-peak period may cause excessive heat loss and higher tariff, the EWH turns on to heat the water before 7pm to generate enough storage for the use during the DR period.

To quantify the reduction in both average power and gross consumption, a baseline hourly load profile needs to be constructed first. Shown in Figure 14, the consumption based on the optimized schedules of 20 previous days in the summer are calculated and divided into hourly profile and the actual load profile for the day with a DR call during 7pm to 8pm. A reduction of 19.66 kWh of electricity can be achieved during the DR period. Thus, for the whole building system, a reduction in average power during the DR period contributed by the EWH system can be expected as well.

4. Conclusion

This paper presents a part of the closed loop electric water heater (EWH) smart scheduling and control system with forecast and robust model predictive control algorithms. The objective is to create an implementable solution of forecasting usage and optimizing controls as a part of a robust and reliable smart building energy management and control system in real-world settings.

To achieve these, an EWH dataset containing data for over 120 days of DHW usage from 77 EWHs gathered at one minute frequency is chosen to demonstrate the methods and results. PROPHET [23] is used for DHW forecasting with a quantified uncertainty range. Results both capture the overall trend and cover the actual usage profile with the uncertainty interval well. A mixed-integer linear programming problem is formulated using a fully mixed single node EWH model to solve for the optimal schedule over the planning horizon and the following control actions with the flexibility to alter between different objectives based on energy programs enrolled. Simulation shows up to about 30% electricity cost reductions over 6 test days with an average comfort fulfillment rate of about 99%. Simulation also shows the capability to shift load profile for reducing average power and gross consumption on short notice. On an example summer day with a demand response (DR) call, testing with a constructed baseline load profile, a reduction of about 20 kWh of electricity is observed during the demand response period.

DHW demand data, while currently very limited, can go a long way in improving EWH control efficiency. By using real data instead of artificially generated demand profiles, our data-driven approach can capture more realistic operating conditions and can be tuned to each building's specific DHW demand behavior. However, measuring volumetric flow, as in the presented dataset, may not be completely sufficient for determining DHW demand in all cases. While in most cases the discharge temperature remains relatively constant, large DHW draws can sometimes lower this temperature, resulting in a higher volume draw to maintain the same enthalpy draw. Thus, data containing additional measurements that determine enthalpy demand may provide a more complete model of DHW demand. Moreover, implementation can require additional ongoing research topics such as hardware and sensor installation, performing state estimation, and reducing the computational burden.

There are also several potential extensions of this work, including the incorporation of onsite generations from photovoltaic systems, day-ahead and real-time electricity pricing, and other more complex and flexible systems and variations[38]. While the general methodology that accounts for uncertainty remains similar to that proposed in this paper, additional modifications to the objective function and system model could expand the potential control objectives. Finally, while this system is designed for aggregated multi-family DHW control, more complex prediction algorithms that can achieve the significantly more difficult task of predicting single-family DHW demand could allow this methodology to provide efficient single-family DHW control as well.

Acknowledgments

The authors acknowledge the support from the National Science Foundation (NSF) under grant 1711546 and the NSF Graduate Research Fellowships Program (to ZEL). The authors also would like to acknowledge Professor Fengqi You at Cornell University for the advice and inspiration on the development of the topic and content of this paper.

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