

# A system of agents for supporting optimization and control of a connected community

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**Abstract**—The residential sector consumes a significant portion of the electricity sold in the United States. Above 60% of the energy used in the sector is used to operate heating ventilation and air conditioning (HVAC) systems and water heating (WH) systems. With the increase of intelligence in the grid and the new decision and control options enabled by the Internet of Things (IoT); control of these devices can be used to support the grid. This paper presents a scalable multi-agent system (MAS) for optimizing HVAC and WH systems while maintaining comfort. It allows a utility to orchestrate the shifting of energy from critical periods without direct control, but instead by using a price signal. The architecture, optimization formulation, implementation strategy and results from an implementation project are discussed.

**Index Terms**— Agents, Demand control, HVAC, Internet of Thing, Load control, Multi-agent systems, Water heating systems

## NOMENCLATURE

|                                     |                                                                                                            |
|-------------------------------------|------------------------------------------------------------------------------------------------------------|
| $\alpha$                            | Solar absorptivity.                                                                                        |
| $a_{00}$ to $a_{16}$                | HVAC performance coefficients.                                                                             |
| $b_{t,Ed}, b_{t,HP}, b_{t,off}$     | Binaries representing the activation of electric coil or heat pump or off.                                 |
| $b_{t,off}, b_{t,cool}, b_{t,heat}$ | Binary representing HVAC is actively off, cooling or heating.                                              |
| $L_2$                               | Capacity loss coefficient (due to duct losses, etc.).                                                      |
| $C_{attic}^{im}, C_{in}^{in}, C_w$  | Thermal capacitance in the attic, mass, air and wall.                                                      |
| $C_{HVAC}$                          | Maximum rated cooling capacity of HVAC.                                                                    |
| $C_w$                               | Thermal capacitance of the water in the water heater.                                                      |
| $D_{t,CYC}$                         | Variable to account for the number of cycles time t.                                                       |
| $D_{t,HP}, D_{t,E}, D_{t,UP}$       | Temperature excursion associated with limits for heat pump, electric coil and upper temperature at time t. |
| $D_{t,HVAC}$                        | Discomfort defined as delta indoor temperature excursion from operating range at time t.                   |
| $\Delta T, t$                       | Time step and time.                                                                                        |
| $h_{roof}, h_{wall}$                | Convection coefficient roof and wall.                                                                      |
| $I_{st}$                            | Solar irradiance.                                                                                          |
| $\rho_t$                            | Price of electricity at time t.                                                                            |
| $P_{t,HVAC}$                        | Electrical power consumed by HVAC at time t.                                                               |
| $P_{t,E}, P_{t,HP}, P_{t,WH}$       | Electrical power consumed by electric coil, heat pump, and water heater at time t.                         |
| $Q_{t,air}$                         | The sensible cooling and heating from the HVAC system.                                                     |
| $Q_{t,cool}, Q_{t,heat}$            | The sensible cooling and heating from the HVAC system.                                                     |
| $Q_{t,max}$                         | Maximum and minimum sensible cooling available from the HVAC system.                                       |
| $Q_{t,min}$                         |                                                                                                            |
| $Q_{t,IHL}$                         | The heating associated with internal heat loads.                                                           |

|                                             |                                                                                                                              |
|---------------------------------------------|------------------------------------------------------------------------------------------------------------------------------|
| $Q_{t,E}, Q_{t,HP}$                         | The heat injected into the water heater by the electric coil and heat pump at time t.                                        |
| $Q_{t,W}$                                   | The heat withdrawal from the water heater due to hot water use.                                                              |
| $T_{t,E}, T_{t,W}$                          | Temperature of the outside environment of the water heater and water at time t.                                              |
| $T_{t,out}$                                 | Temperature of the outside.                                                                                                  |
| $T_{t,attic}, T_{t,in}$                     | Residential building attic, indoor, mass, and wall temperature at time t.                                                    |
| $T_{t,max}, T_{t,min}$                      | Maximum and minimum indoor operating temperature.                                                                            |
| $T_{t,sol,w}, T_{t,sol,r}$                  | Temperature as a combination of outside temperature and solar irradiance on building wall and roof.                          |
| $R_{attic}, R_{roof}, R_{im}, R_w, R_{win}$ | Thermal resistances of the residential building attic, roof, mass, walls (divided by 2), and window.                         |
| $R_w$                                       | Thermal resistance of the water heater walls.                                                                                |
| $W_{CYC}, W_{HP}, W_{EL}, W_{UP}$           | Weight factor associated with cycling, heat pump and electric minimum water temperatures, and maximum operating temperature. |
| $W_p, W_D$                                  | Weight factor associated with price and discomfort.                                                                          |

## I. INTRODUCTION<sup>1</sup>

The electric grid has seen a significant advancement of intelligence, communication, and control capabilities within the last decade [1], [2]. Intelligent systems are being pushed to the grid edge through the adoption of the Internet of Things (IoT) and the increasing interest in giving consumers controllability and accessibility of their devices. Of particular interest is the residential sector which has observed continuing growth and already accounts for 38% [3] of electricity purchased in the United States (the highest of any sector.)

As the number of intelligent systems within the electric grid continues to grow, the utilization of distributed control techniques to solve grid challenges has also seen a surge [4]. Multi-agent systems (MAS) represent one example approach and have been widely used [5]–[7]. An inherent quality of MAS is the ability to subdivide complex problems. This property is derived from four characteristics of agents outlined in [8]: autonomy, social ability, reactivity, and pro-activity. These traits create self-contained, goal-orientated entities that are: 1) able to function without direct intervention, 2) able to communicate with other entities, and 3) able to react to environmental conditions. Subdividing complex problems has

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become increasingly attractive as parallel computing capabilities have increased [9]. Furthermore, the significant growth in intelligent devices has increased the requirements of the size, scale, and complexity of the overall computational problem [10].

Five categories have been developed for MAS grid applications [11]: control, operation, and management; system protection; monitoring; security; and demand response management. In [12], grid control, operation, and management are performed by agents within a smart grid. Measurements are collected and communicated to the resources to establish relevant settings for performing optimal reactive power control. Self-healing applications are demonstrated in [13], [14] via agents that collect data, assess the current status of the grid, and formulate the actions needed to restore grid stability. Microgrid optimization [15] and control [16], [17] approaches have also been tackled by MAS. In general, individual agents monitor and control the loads and energy sources in coordination with an aggregator agent and other grid agents in a hierarchal design. Distributed protection based on a MAS has also been explored and presented in [18], [19]. In this work, the agents using peer-to-peer communication mitigate risk associated with central controller failure. Grid monitoring systems with diagnostics have also been developed utilizing MAS [20]. Agents have been used to integrate multiple intelligent system techniques and legacy data sources and systems while also being able to support new techniques, datasets, and sensors. Auction based systems for demand response applications [21], [22] use auctioneer agents that coordinate sales in a virtual market and other agents for support. Priority based shedding is enacted through a coordinator agent in [23]. The coordinator agent receives a load reduction request and then determines based on the priority and the current consumption how to best meet the demand. In [24], a system of agents has been developed to support independent charging strategies for electric vehicles (EV).

In this paper, a MAS has been developed to optimize and control residential building heating, ventilation, and air conditioning (HVAC) and water heater systems while ensuring comfort limits are maintained. The goal is to create a scalable system with the ability to incentivize energy consumption changes or shifts through a dynamically changing pricing profile. In this way, a utility can orchestrate energy reduction during critical anticipated periods without directly controlling the residential loads. This paper presents the MAS architecture, optimization formulation, and implementation strategy, and discusses an actual implementation in a community through a presentation of measured results and supplementary simulation. A final discussion on challenges encountered provides for future work opportunities.

## II. BACKGROUND ON LOAD CONTROL

There have been two primary means of implementing load control in residential buildings: direct and indirect load control. Direct load control strategies are performed by directly assessing the load from a central system and issuing ‘switch-off’ type signals. This type of approach has been used for decades as a means to manage peak [25]. However, this

approach has also been met with consumer anxiety as occupant discomfort is often neglected [26] and indoor temperature data is not typically available at that scale or used in evaluating the control. To alleviate this problem model predictive estimation [27] and homeowner set boundaries have been investigated [28].

Indirect load control uses methods to manage residential loads without sending direct control commands. These methods are generally based on motivational techniques to incentivize response (such as a price signal). Economic optimization techniques considering load optimization have been performed in both multi-objective mix-integer (MIP) [29]-[30] and in particle swarm optimization (PSO) [31]. Precooling to reduce HVAC operation during the high price period has been investigated by the authors in [26]. A linear-sequential-optimization-enhanced multiloop algorithm with linear comfort constraints is present in [32] for scheduling water heating. The authors of this work found that most other approaches used nonlinear optimizations while others neglected to consider the comfort of the end user. Since the ability to alter the price signal is not a typical utility feature [33], other techniques have been created to support optimization including: a) MPC with game theory [34] and b) auction-based techniques [35].

As shown in [33], using price signals to drive indirect load control can be a promising approach. A price signal can be generated that allows the individual homeowner to selfishly optimize while the social welfare is maximized. This method provides performance individuality (each homeowner can optimize without consideration of a neighbor). However, to achieve the best performance, a price signal must be generated to obtain the desired outcome.

Real-time pricing control systems have also been demonstrated in [36] and evaluated by the authors in [37]. In [37], the authors found that existing control implementations in [36] have not been driven by the price or predictive algorithms, but instead are completely reactionary. This potentially misses opportunities of storing energy in the form of precooling and preheating.

A meter gateway architecture which integrates advanced meter infrastructure (AMI), building automation systems (BAS), and embedded control is demonstrated in [38]. In this approach, decision-making can be performed at various levels of the hierarchy: a) smart devices, 2) BAS, or 3) aggregator. The location of the intelligence and decision-making is determined based on the needed actions and computational capability. Load control frameworks using a 3 layer structure have been proposed by the authors in [39], [40].

Agent based systems have been used to facilitate many types of load control, with many different architectures, layers, and hierarchal designs [41]-[43]. In [44], agents represented buildings in a microgrid. The authors of [42] choose a hierarchical agent structure to reduce data management complexity. Data is processed and simplified at the lowest levels before being transmitted to higher level decision-making systems. Agents still have autonomy to decide and operate on local criteria and environment based on available data. The architecture presented in [41] operates at a higher layer of

abstraction treating loads as entities that connect to a control relay. The transmission network supports a central energy management system which represents the highest layer modeled in this work. The author suggest that hierarchal systems are prone to communication interruptions and utilize a MAS to autonomize the system in a decentralized approach. In [43], the authors identify key characteristics required to transition the current grid to be smart: intelligent, efficient, and flexible. As a result, the authors also propose a MAS architecture with distributed intelligence and dynamic decision-making capabilities as a solution.

Much of the literature in load control, especially in the residential sector, is based on simulations and small experiments. While simulation can be useful in establishing basic operational principles and basic control philosophies, real world implementation and operational challenges often provide additional insight. In this work, a real-time MPC formulation with agents is presented for a community of sixty-two single-family detached homes. This neighborhood is shown in Fig. 1. Given that space conditioning and water heating account for approximately two-thirds of energy consumption [45], these loads became the primary targets for optimization and control.

Each home has been fitted with a Rheem Professional Prestige® Hybrid Electric water heater and a Carrier Greenspeed variable-speed heat pump [46]. The 80-gallon water heater supports several modes: Heat Pump, Electric, High Demand, and Energy saver [47]. The Carrier system supports the conventional heating, cooling, and auto modes along with the ability to enter schedules. Since each home contains identical HVCA, water heater loads and building construction is similar, the risk of a single home dominating over another was not deemed significant. The novelty in this work is associated with the collection of agents that intercommunicate, optimize, and learn to support residential building owner dynamic pricing, demand side management in a real-world implementation. This system has been constructed to be scalable and hostable in cloud-based systems and has been deployed. The agent framework is presented in the next section.

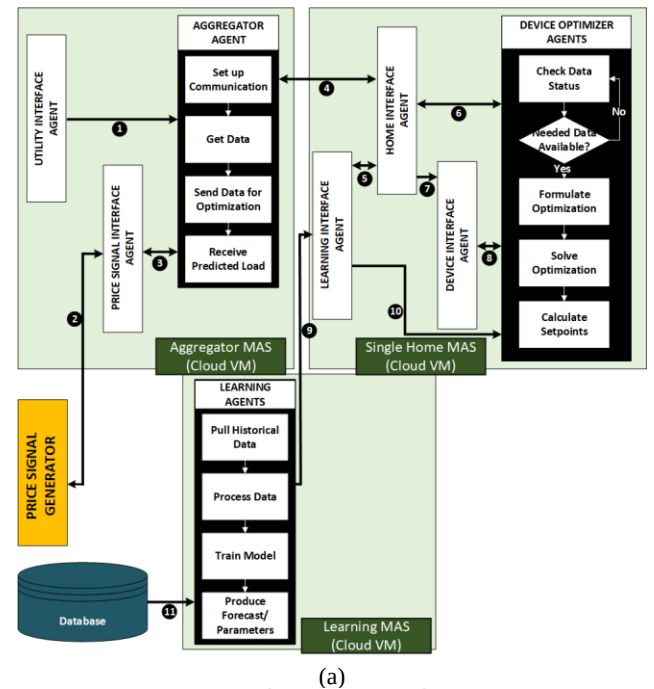


Fig. 1. Connected neighborhood in Hoover, AL

### III. AGENT FRAMEWORK

A framework consisting of multi-agent systems (MAS) has been developed to perform optimization, communications, and controls for residential loads (HVAC and water heaters) to support a dynamically changing price signal. The framework

consists of three different MAS configurations: single home, learning, and aggregator as shown in Fig. 2a and described in Table I. The data flows denoted by the arrows in Fig. 2a with their corresponding messaging details in Fig. 2b are facilitated via the communication bus linked to application programming interfaces (API). In the developed MAS architecture, only a single aggregator and learning MAS are present. The aggregator MAS behaves as the interface between the single home MAS and the price signal generator and is the collector and distributor of pricing information and other data. The learning MAS collects and processes data using a suite of algorithms to develop model characteristic information and projections for improving the accuracy of the optimization. The single home MAS (which is hosted for each residential building within the neighborhood separately) performs the optimization, control, and prediction for the home, using separate device interface and optimizer agents for each device, namely the water heater and HVAC. Each MAS is deployable on a virtual machine that can be hosted in the cloud for instant scalability. Rotating keys provide for security and a unique set of addressing and identification keys allow for auto-configuration.



(a)

|    | ←                                                                           | →                                                                                       |
|----|-----------------------------------------------------------------------------|-----------------------------------------------------------------------------------------|
| 1  | Credentials, Temperature forecast, Solar forecast, Aggregator configuration |                                                                                         |
| 2  | Total Electricity, Iteration                                                | Price signal, Acceptance, Iteration                                                     |
| 3  | Total Electricity, Iteration                                                | Price signal, Acceptance, Iteration                                                     |
| 4  | Total Electricity, Iteration                                                | Price signal, Acceptance, Iteration, Temperature forecast, Solar Forecast               |
| 5  | Home ID, Credentials                                                        | Electricity Forecast                                                                    |
| 6  | Optimized Electricity Forecast for Device                                   | Home ID, Price Signal, Iteration, Credentials, Temperature Forecast, Solar Forecast     |
| 7  |                                                                             | Home ID, Credentials, Acceptance                                                        |
| 8  | Device Setpoint, Device Mode                                                | Current Temperature, Current Mode, T <sub>max</sub> , T <sub>min</sub>                  |
| 9  |                                                                             | Electricity Forecast, Building parameters & Heat Load Prediction / Hot Water Prediction |
| 10 |                                                                             | Building parameters & Heat Load Prediction / Hot Water Prediction                       |
| 11 |                                                                             | Site data, Meter data, Weather data, Building parameters & Heat Load / Hot Water        |

Fig. 2. Data exchange and processing within the agent system: (a) diagram for data flow and (b) data flow key

Each agent in the developed MAS framework is represented by a separate program that supports autonomy, reactivity, social ability, and pro-activity. All of the agents utilize a set of looping and threading functions that react to changes in information communicated either from inside the MAS or from outside interconnections. This type of architecture supports expansion to many types of loads and resources. The following subsections describe the architecture and key features provided by agents and the corresponding MAS in more detail.

TABLE I. Multi-Agent Systems to Support Community

| MAS         | Number    | Purpose                                                                                                                                                                         |
|-------------|-----------|---------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|
| Single Home | 1 x Homes | Multi-agent system that collects and optimizes HVAC and water heater utilization for a specific residential building based on set of parameters and the current price signal.   |
| Aggregator  | 1         | Multi-agent system that collects the price signal from a system generator and other data sets (such as weather) and distributes this information to the various single home MAS |
| Learning    | 1         | Multi-agent system that performs collects historical information to project a forecast for needed parameters for optimization.                                                  |

#### A. Single Home Multi-Agent System

The single home MAS is composed of agents that coordinate control and optimization for the HVAC and water heater. These agents include home interface, learning interface, water heater interface and optimizer, and HVAC interface and optimizer agents. In this implementation, each home has a dedicated single home MAS which has been designed to operate autonomously without the need for significant configuration. Each single home MAS is identical on launch but can inherit unique credentials and configurations through a utility API portal. This is a critical aspect to scalability as each homeowner has a separate set of log-in credentials for the devices, user inputs for bounding the control problem, residential building design for the model, and usage patterns of electrical consumption. These datasets and credentials are needed to communicate to the vendor APIs and to support optimization and control of the HVAC and water heater. Specific agent descriptions are provided in Table II.

The agents have been classified based on three types: interfaces, optimizers, or artificial intelligence agents. The interface agents with the single home MAS are responsible for collecting and posting data either to/from equipment manufacturer vendor APIs or the system communication bus that provides intra-system communication capabilities (communication between VMs utilizes Microsoft Azure Service Bus). Communications on the communication bus consist of 24-hour, 5-minute data arrays of anticipated electrical consumption, projected price signal, and forecasted weather (solar irradiance and temperature). Inter-system communications are performed through a publish/subscribe open-protocol zero message queueing (zmq).

The optimizer agents use a model predictive control (MPC) approach to perform the optimal control of HVAC and water heaters. Electrical equivalent models for the building and water

heater have been developed in previous work [48] and capture the thermal energy transfer of the systems. Performance data on the heat and sensible cooling generation based on electricity consumption is also included in the optimization formulation as well as forecasted hot water utilization and heat loading. This optimization is discussed in more detail in IV.

TABLE II. Single Home MAS Agents

| Agent                   | Purpose                                                                                                                                                                                          |
|-------------------------|--------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|
| <i>Interface Agents</i> |                                                                                                                                                                                                  |
| Home Interface          | Interface to the communication bus for system to system communications. Primarily used to communicate price signal and anticipated electricity consumption.                                      |
| HVAC Interface          | Interface to the HVAC vendor API. Gets measurement data and status of the HVAC and posts control.                                                                                                |
| Water Heater Interface  | Interface to the water heater vendor API. Gets measurement data and status of the water heater and posts control.                                                                                |
| Learning Interface      | Interface to the learning system data. Gets learned model information and forecast data.                                                                                                         |
| <i>Optimizer Agents</i> |                                                                                                                                                                                                  |
| HVAC Optimizer          | Utilizes building specifications, forecasted weather data, building parameter data, price forecast, and HVAC status data to optimally schedule HVAC and provide expected electrical consumption. |
| Water Heater Optimizer  | Utilizes predicted water consumption, price forecast, and Water Heater status data to optimally schedule Water Heater and provide expected electrical consumption.                               |

#### B. Learning Multi-Agent System

The learning MAS utilizes agents to provide tuned information for each residential building regarding the thermal envelope [49] and forecasted information on hot water usage and electricity and heat load patterns [50]. The forecasting agents utilize time-varying clustering-based Markov models to create forecasts for the whole day (5-minute interval data). These forecasts are used as an input to the MPC optimization algorithm. At the initialization of the learning, the forecast agents query the past two weeks of data through a utility API to train the model and develop forecasts based on the generated model. The new forecast models are sent back to the API to be used periodically for the optimization. Due to the large amount of metering data and the time associated to query this data from API, a copy of the queried and processed metering data is maintained on the learning MAS VM locally. The new data is queried and appended to this dataset periodically.

The tuning of the building thermal model is performed through regression analysis as discussed in [44]. Data on historical weather, HVAC consumption, and measured indoor temperature from the thermostat are collected via the utility API and used to create electrical equivalent representations of the building envelope. These are posted to the utility API to be later collected for optimization. Learning MAS agents are described in Table III. The next section presents the aggregator MAS.

TABLE III. Learning MAS Agents

| Agent                                          | Purpose                                                                                                                                       |
|------------------------------------------------|-----------------------------------------------------------------------------------------------------------------------------------------------|
| <i>Artificial Intelligence Agents</i>          |                                                                                                                                               |
| Hot Water Predictor                            | Produces a forecast estimation of the hot water usage in time based on historical flow meter data.                                            |
| Internal Heat Load and Electricity Consumption | Produces a forecast estimation of heat load within the home and other load electricity consumption based on metered circuit level data.       |
| Building Model Parameters                      | Estimates the building parameters for the MPC formulation based on historical weather data and HVAC, WH and other metered circuit level data. |

### C. Aggregator Multi-Agent System

The aggregator MAS set of agents is chiefly responsible for distributing and collecting information. Price signals and weather forecast information are distributed to each single home MAS through the aggregator agent via the intra-agent system communication bus. The price signal is collected from the price signal generator. The optimized and forecasted electrical consumption of the all the residential buildings is also collected and summed. This value is provided to the price signal generator. Specific agent descriptions are provided in Table IV.

TABLE IV. Aggregator MAS Agents

| Agent                   | Purpose                                                                                                                                          |
|-------------------------|--------------------------------------------------------------------------------------------------------------------------------------------------|
| <i>Interface Agents</i> |                                                                                                                                                  |
| Utility Interface       | Pulls data utility AP including weather and communication bus credentials                                                                        |
| Price Signal Interface  | Communicates to the price signal generator.                                                                                                      |
| Aggregator              | Sets up communications to each Single Home VM and issues weather data, price signal, and iteration while receiving predicted load and iteration. |

## IV. DEVICE AGENT OPTIMIZATION AND CONTROL

There are several goals in the formulation of the optimization problem: 1) deliver optimal control of HVAC and water heater considering consumer economics and comfort; 2) utilize open-source techniques and solvers; and 3) reduce the computational needs in the platform to save on deployment cost while ensuring the results can be determined in a short time frame (less than 2 mins). For the first goal, the multi-objective optimization formulation for the water heater and HVAC included both energy cost and temperature excursions outside of desired operational range. The second goal relied on the application of open-source tools to keep the cost of implementation low. In this case (COIN|OR) has been used as the open-source solver [51] and PuLP [52] as the code interface. The entire platform is coded in Python. Finally, to keep the computational requirements minimized, the optimization formulations are all linearized using electrical equivalent circuits and which have previously been used in [48] as shown in Fig. 3 In the next sections, details of the optimization formulation are presented.

### A. Water Heater Optimization Formulation

The control capabilities of the hot water heater are based on two operational modes that are able to contribute heat to internal water temperature: 1) efficient heat pump mode and 2) less efficient but fast electric mode. The electrical equivalent model

that supports estimation of the heat loss is provided in Fig. 3. Discussion of the optimization formulations previously introduced in [53] are in the next sections.

#### 1) Objective Function

The multi-objective function defined for water heater optimization and control has been derived as (1):

$$\min(W_P \sum_{t=0}^T P_t^{WH} * \rho_t + W_{HP} \sum_{t=0}^T D_t^{HP} + W_{EL} \sum_{t=0}^T D_t^{EL} + W_{UP} \sum_{t=0}^T D_t^{UP} + W_{CYC} \sum_{t=0}^T D_t^{CYC}) \quad (1)$$

The formulation is focused on minimizing the electrical power consumption costs (a product of the electrical energy or electrical power,  $P_t^{WH}$ , over a time interval and proposed price,  $\rho_t$ ) and discomfort factors ( $D_t^{HP}$ - trigger for minimum temperature for heat pump activation,  $D_t^{EL}$ - trigger for minimum temperature for electric mode operation,  $D_t^{UP}$  – and trigger for turning off the water heater due to overtemp. A cycling impact,  $D_t^{CYC}$ , has been included as part of the objective formulation to reduce potential cycling impacts on equipment. The weights,  $W$ , for the objectives have been tuned experimentally.

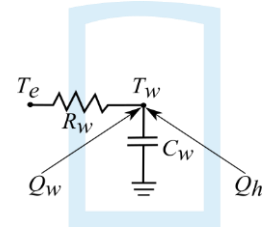


Fig. 3. Water heater model for MPC formulation

#### 2) Water Heater Optimization and Control

The auxiliary variables associated with temperature limits are presented in (2):

$$D_t^x = \begin{cases} D_t^{HP} \geq T_{minHP} - T_t^W, D_t^{HP} \geq 0, \text{heat pump} \\ D_t^{EL} \geq T_{minE} - T_t^W, D_t^{EL} \geq 0, \text{electric} \\ D_t^{UP} \geq T_t^W - T_{max}, D_t^{UP} \geq 0, \text{turn off} \end{cases} \quad (2)$$

The purpose of the constraints in (2) is to primarily drive the operation of the water heater in heat pump mode with transitions into electric heat during large, unexpected water draws. Hence,  $T_{minHP}$  was set to 48.9°C and  $T_{minE}$  was set to 32.2°C. To incorporate impacts of water draws into the optimization, a thermal model of the water heater internal temperature has been developed as (3):

$$T_{t+1}^W = \frac{\left(\frac{T_t^e - T_t^W}{R_W} + Q_t^W + Q_t^H\right)\Delta t}{C_W} + T_t^W \quad (3)$$

This thermal model is based on the water temperature,  $T_t^W$ , heat injected into the water by either the electric element or heat pump,  $Q_t^H$ , heat extracted through the utilization of hot water,  $Q_t^W$ , thermal resistance of the hot water tank,  $R_W$ , and thermal capacity of the tank water,  $C_W$ .

Water heating ( $Q_t^H$ ) and electricity consumption ( $P_t^H$ ) are either derived from the heat pump ( $Q_t^{HP}$  and  $P_t^{HP}$ ) or the electric element ( $Q_t^E$  and  $P_t^E$ ). This is captured by (4):

$$\begin{aligned} Q_t^H &= Q_t^{HP} + Q_t^E \\ P_t^H &= P_t^{HP} + P_t^E \end{aligned} \quad (4)$$

The water heater provides for direct control of the modes in either heat pump, electric, or off. Binaries are used to capture heat pump ( $b_t^{HP}$ ) and electric ( $b_t^E$ ) modes through (5):

$$1 \geq b_t^E + b_t^{HP} \quad (5)$$

Since the heating capacity and electric power of the heat pump are dependent on the temperature of the water, a generalizable linear equation and deactivation limits (maximum limits times a binary) are used as shown in (6) and (7):

$$Q_t^{HP} = \begin{cases} \leq 1500 - 8.0 \times T_t^w \\ \leq 3500 \times b_t^{HP} \\ \geq 0 \end{cases} \quad (6)$$

$$P_t^{HP} = \begin{cases} \leq 3500 \times b_t^{HP} \\ \leq 1190 \times b_t^{HP} - 0.689 \times Q_t^{HP} \\ \geq 0 \end{cases} \quad (7)$$

The parameters for the linear relationship for the heat pump in (6) and (7) are directly related to the heat pump design and are derived experimentally. In the case of the electric element the heating capability varies minimally and as such is treated as a constant (8):

$$Electricity = \begin{cases} Q_t^E = 5000 \times b_t^E \\ P_t^E = 5000 \times b_t^E \end{cases} \quad (8)$$

Temperature reading for the upper and lower sections of the tank are available and are averaged to provide the starting initial temperature for the optimization. Cycling constraints are captured as (9):

$$D_{t+1}^{cycle} = \begin{cases} \geq 0 \\ \leq b_t^{HP} \\ \geq b_t^{HP} - b_{t+1}^{HP} \\ \geq 1 - b_{t+1}^{HP} \end{cases} \quad (9)$$

In (9) positive values are accrued when the heat pump transitions from off to on. The constraints (4)-(9) represent the operational behavior of the water heater in both heat pump and electrical modes while minimizing cycling. The electrical consumption,  $P_t^{WH}$ , of the water heater is the optimization output which is used to make control decisions. This value is used to determine the issued control setpoints as provided in TABLE V.  $T_{top=0}$  is the temperature at the top of the water heater tank at  $t=0$ .

TABLE V Adjustment of Tset to obtain desired control for water heater

| Optimization Output        | Setpoint                  |
|----------------------------|---------------------------|
| $P_{WH} = 0$ (standby/off) | $T_{set} = T_{minHP}$     |
| $P_{WH} !> 0$ (electric)   | $T_{set} = T_{top=0} + 7$ |
| $P_{WH} !> 0$ (heat pump)  | $T_{set} = T_{max}$       |

## B. Heating, Ventilation, and Air Conditioning Optimization Formulation

The HVAC system, in this work, supports three different operational modes: Heat, Cool, and Auto. In the development of the model formulation, an electrical equivalent model is used as shown in Fig. 4. Discussion of the optimization formulations previously introduced in [54] are in the next sections.

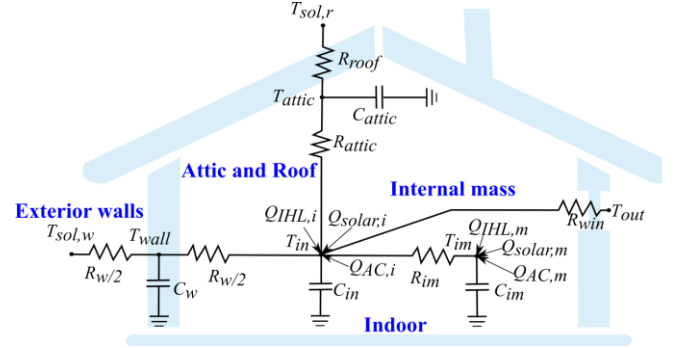


Fig. 4. Residential building model for HVAC optimization

### 1) Objective Function

The multi-objective function defined for HVAC optimization and control has been written as (10):

$$\min(W_P \sum_{t=0} P_t^{HVAC} \rho_t + W_D \sum_{t=0} D_t^{HVAC}) \quad (10)$$

The formulation is focused on minimizing the electrical power consumption costs (a product of the electrical energy or electrical power,  $P_t^{HVAC}$ , over a time interval and proposed price,  $\rho_t$ ) and discomfort factors ( $D_t^{HVAC}$ - trigger when minimum or maximum temperature for the HVAC is reached. The weights,  $W$ , has been determined experimentally for the HVAC optimization to ensure temperature comfort is maintained.

### 2) Heating, Ventilation, and Air Conditioning System Constraints

The constraints of the HVAC optimization model focus on capturing the thermal response of the building envelope and temperature control ranges. The temperature limits are retrieved from the HVAC thermostat schedule,  $T_{min}$  for heating and  $T_{max}$  for cooling.

An auxiliary variable associated with temperature limits has been added to accrue cost with temperature violations (11):

$$D_t^{HVAC} = \begin{cases} \geq T_t^{in} - T_t^{max} \\ \geq T_t^{min} - T_t^{in} \\ \geq 0 \end{cases} \quad (11)$$

These comfort constraints capture additional cost when: 1) the maximum wanted temperature,  $T_t^{max}$ , is exceed and 2) the minimum wanted temperature,  $T_t^{min}$ , is passed.

Outside temperature,  $T_t^{out}$ , and solar irradiance,  $I_{st}$ , forecast data are provided by the utility API and are used to determine building roof,  $T_t^{sol,r}$ , and wall,  $T_t^{sol,w}$ , surface temperatures as shown in (12) and (13):

$$T_t^{sol,w} = T_t^{out} + I_{st} \times \frac{\alpha_{wall}}{h_{wall}} \quad (12)$$

$$T_t^{sol,r} = T_t^{out} + I_{st} \times \frac{\alpha_{roof}}{h_{roof}} \quad (13)$$

An electrical equivalent model for capturing heat transfer for the building (Fig. 4) is used to calculate the exterior wall temperature,  $T_t^{wall}$ , attic temperature,  $T_t^{attic}$ , indoor thermal mass temperature,  $T_t^{mass}$ , and indoor air temperature,  $T_t^{in}$ . These constraints are presented in (14) – (17):

$$T_{t+1}^{wall} = \left( \frac{T_t^{sol,w} - T_t^{wall}}{\frac{R_w}{2}} + \frac{T_t^{in} - T_t^{wall}}{\frac{R_w}{2}} \right) \times \frac{\Delta t}{C_w} + T_t^{wall} \quad (14)$$

$$T_{t+1}^{attic} = \left( \frac{T_t^{in} - T_t^{attic}}{R_{attic}} + \frac{T_t^{sol,r} - T_t^{attic}}{R_{roof}} \right) \times \frac{\Delta t}{C_{attic}} + T_t^{attic} \quad (15)$$

$$T_{t+1}^{mass} = \left( \frac{T_t^{in} - T_t^{mass}}{R_{im}} \right) \times \frac{\Delta t}{C_{im}} + T_t^{mass} \quad (16)$$

$$T_{t+1}^{in} = \left( \frac{T_t^{wall} - T_t^{in}}{\frac{R_w}{2}} + \frac{T_t^{attic} - T_t^{in}}{R_{attic}} + \frac{T_t^{mass} - T_t^{in}}{R_{im}} + \frac{T_t^{out} - T_t^{in}}{R_{win}} + L_2 Q_t^{air} \right) \times \frac{\Delta t}{C_{in}} + T_t^{in} \quad (17)$$

The  $R$  and  $C$  values within the equations represent the thermal resistance and capacitance in the model. A relationship between the outdoor temperature and minimum and maximum limits for sensible cooling and sensible heating have been derived into a linear representation as presented in (19) and (20):

$$Q_t^{max} = a_{00} + a_{01}T_t^{out} + a_{02}T_t^{out^2} + a_{03}T_t^{out^3} + a_{04}T_t^{out^4} + a_{05}T_t^{out^5} + a_{06}T_t^{out^6} \quad (18)$$

$$Q_t^{min} = a_{10} + a_{11}T_t^{out} + a_{12}T_t^{out^2} + a_{13}T_t^{out^3} + a_{14}T_t^{out^4} + a_{15}T_t^{out^5} + a_{16}T_t^{out^6} \quad (19)$$

These constraints are based on directly on determined values from a forecast and be used to numerically calculate the minimum and maximum limits. Constraints for the sensible cooling,  $Q_t^{cool}$ , and sensible heating,  $Q_t^{heat}$ , for different control mode options as a function of the limits and binaries (where  $b_t^{cool}$  is cooling binary and  $b_t^{heat}$  is the heating binary) for the HVAC system are presented in Equations (20)-(27).

Cool Mode Only:

$$Q_t^{heat} = 0 \quad (20)$$

Cool or Auto Modes:

$$Q_t^{cool} = \begin{cases} \leq Q_t^{max} b_t^{cool} \\ Q_t^{min} - Q_t^{min} b_t^{cool} \\ \geq 0 \end{cases} \quad (21)$$

$$b_t^{cool} + b_t^{cool} \leq 1 \quad (22)$$

Heat Mode Only:

$$Q_t^{cool} = 0 \quad (23)$$

Heat or Auto Mode:

$$Q_t^{heat} = \begin{cases} \leq Q_t^{max} b_t^{heat} \\ \geq Q_t^{min} - Q_t^{min} b_t^{heat} \\ \geq 0 \end{cases} \quad (24)$$

$$b_t^{heat} + b_t^{heat} \leq 1 \quad (25)$$

Off:

$$Q_t^{cool} = 0 \quad (26)$$

$$Q_t^{heat} = 0 \quad (27)$$

Binaries restrict the HVAC to be considered in cooling mode, heating mode, or off (28):

$$b_t^{cool} + b_t^{heat} + b_t^{off} \leq 1 \quad (28)$$

The sensible cooling and heating are combined into single variable to allow for heating or cooling as show in (29):

$$Q_t^{air} = Q_t^{heat} - Q_t^{cool} \quad (29)$$

A coefficient of performance (COP) is used to link the cooling and heating outputs to electrical consumption ( $P_t^{HVAC}$ ). The HVAC electrical consumption for the different modes are provided in (31)-(33).

For Heating:

$$P_t^{HVAC} = (P_t^{minheat} b_t^{heat} + P_t^{maxheat}) - \left( P_t^{minheat} \times \frac{Q_t^{heat} - Q_t^{minheat} b_t^{heat}}{Q_t^{maxheat}} \right) \quad (31)$$

For Cooling:

$$P_t^{HVAC} = (P_t^{mincool} b_t^{cool} + P_t^{maxcool}) - \left( P_t^{mincool} \times \frac{Q_t^{cool} - Q_t^{mincool} b_t^{cool}}{Q_t^{maxcool}} \right) \quad (32)$$

For Off

$$P_t^{HVAC} = 0 \quad (33)$$

Values obtained from  $P_t^{HVAC}$  are used to perform control setpoints decisions. These are discussed in the next section.

### 3) HVAC Control

Due to the nature of the variable speed capability of the HVAC, a mapping of the setpoint relationship to the measured temperature and sensible cooling has been developed as shown in TABLE VI. This provided a means to utilize the calculated optimal sensible cooling and link this to a setpoint for control. When cooling is not needed for optimization, the temperature setpoint is set above the measured temperature. This eliminates the need to completely deactivate the HVAC system, preserving a safe controllable approach with loss of communications. In the next section, experimental results of the agent system and the formulation of the optimization and control are presented.

TABLE VI Adjustment of Tset to obtain desired control for HVAC

| Optimization Output [W]            | Temp [°C] setpoint versus Measured indoor Temp |
|------------------------------------|------------------------------------------------|
| $Q_{cool}(1) < 4000$ (standby/off) | $T_{set} = T_{meas} + 1.1111$                  |
| $4000 \leq Q_{cool}(1) < 7000$     | $T_{set} = T_{meas} - 0.1667$                  |
| $7000 \leq Q_{cool}(1) < 8000$     | $T_{set} = T_{meas} - 0.3333$                  |
| $8000 \leq Q_{cool}(1) < 9000$     | $T_{set} = T_{meas} - 0.5556$                  |
| $Q_{cool}(1) \geq 9000$            | $T_{set} = T_{meas} - 0.8333$                  |

## V. EXPERIMENTAL RESULTS

The MAS framework has been deployed in a utility hosted virtual machine environment behind a set of firewalls for security purposes. Each individual VM instance is a Linux-based single core machine with 2 GB of random-access memory (RAM). In this environment, each of the 62 homes in the neighborhood has a dedicated set of ids and tokens. Setpoints for devices are sent through the device manufacturer APIs. Each agent sends data to the utility API for recording and verifying continued operations.

During the experiment, the optimization agents are activated as week-on and week-off periods to collect potential data for baseline and post evaluation. This is conducted per season to ensure temperature and solar irradiance similar days could be established.

Data and control limits have been imposed by the vendor systems to a frequency of 5-minutes. Hence, optimization and dispatch have been adjusted to occur every 5 minutes with a forecast window of 24 hours at 5-minute steps. This led to a ~60% utilization of the CPU and ~43% of RAM for the home VMs and 50% CPU and 28% RAM for the aggregator. Running the optimization at this frequency allows for corrections in poor forecasting, error in the MPC models, and adjustments in price signals.

As part of this work, a method of detection for customer dissatisfaction has been developed. Customers have been asked to utilize HVAC schedules as a primary means for comfort and to make a direct setpoint change on the thermostat when not satisfied with the operation. This represented an ‘over-ride’ by the customer. HVAC and water results are discussed in the next sections.

### 1) Single HVAC comparison of measured results

Data collected for HVAC operations for an individual home and neighborhood are presented in Fig. 6-Fig. 8. Similar temperature and solar irradiance days, shown in Fig. 5, for on-and-off weeks have been found to ensure a fair comparison of data. As shown, a high price period (as per the utility typical time-of-use) was initiated between 1pm and 7pm to reduce peak during this time interval.

A direct comparison of a single home consumption shows the HVAC optimization and control performance based on measured data. Up to 9AM, the difference in schedule is minimal (Fig. 7) with power consumption also almost identical (Fig. 6). At this point, the optimization maintains the operating temperature at 72F (based on a 2 degree of Fahrenheit limit constrained by the auxiliary variable) while the user controls the temperature to 70F incurring additional consumption and a spike in consumption. Shortly before noon (more than an hour before the peak price event) the optimization enacts precooling

as the optimization objective tries to drive the anticipated cost down by reducing the power consumption projected with a high price signal. This spurs additional electrical consumption to spike above the user scheduled consumption. However, as the peak price nears, the optimization enacts a power turn off by raising the temperature to deactivate the HVAC system and thereby reducing consumption during the high-cost period. At approximately 5pm, cooling is reenacted to ensure that the comfort is maintained, and the optimization consumption ends up higher than the user setting. The need for the HVAC to be reactivated more than an hour before the end of the critical price period indicates that there is not enough stored thermal inertia within the building as described by (14)-(17) to ride-through the 6 hours peak period.

### 2) Whole neighborhood HVAC comparison of measured results with simulation

While significant reduction is observed at the single home level, not all homes participated in the optimization and control period as shown in Fig. 8 (challenges with homeowner engagement are discussed in the next section). A simulation has been performed to compare complete neighborhood participation and load control potential based on the temperature and solar irradiance. As shown, the optimized neighborhood electrical consumption takes on a similarly lower consumption (as the case with the single home example) early in the peak price period but slightly overshoots the user scheduled case during the period.

A comparison of the homeowner economics shows a much clearer picture of the benefits of the control. Table VII shows a cost comparison of the optimization versus the basic schedule. Optimization was able to reduce the homeowner cost by a factor of almost 65%.

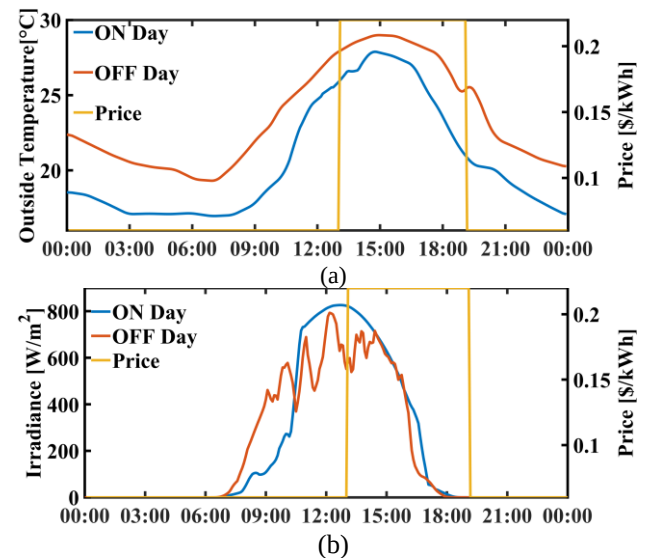


Fig. 5. (a) Temperature outside and (b) Irradiance on similar weather days

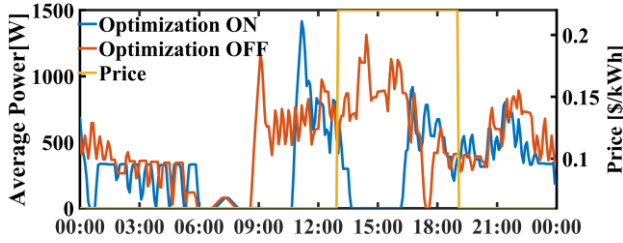


Fig. 6. Measured HVAC demand from a single home on similar days with the optimization ON and with it OFF

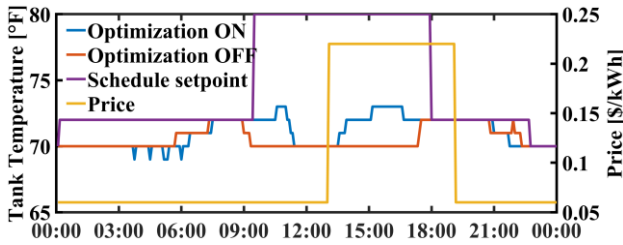


Fig. 7. Measured HVAC temperature versus schedule from a single home on similar days with the optimization ON and with it OFF

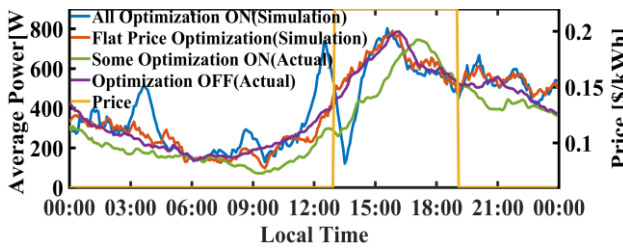


Fig. 8. The average neighborhood HVAC demand (cooling mode) comparing similar days with the optimization only ON for some home, OFF for all home and a simulation of all homes with optimization ON

TABLE VII Table comparison of economics

|              | Optimization OFF (Actual) | Optimization ON (Simulation) |
|--------------|---------------------------|------------------------------|
| Water heater | \$4.00                    | \$2.12                       |
| HVAC         | \$6.68                    | \$2.33                       |

### 3) Single Water heater measured results

Data collected for water heater operations for an individual home and neighborhood are presented in Fig. 9-Fig. 12. Direct comparisons of data in this case are more difficult as hot water use profiles are not directly comparable. Instead, a comparison of on and off periods of the optimization has been performed against simulation to best demonstrate the results of the framework. As shown in Fig. 9 and Fig. 10, a single home water heater optimization results shows that the hot water preheats (the optimization starts heating almost 4 hours in advance of the critical peak price as the heat pump thermal contribution is significantly lower compared to electric as presented in (6) and (8)). The temperature is able transition from approximately 105F to 130F before the peak price event (due to challenges with the latency in control the deactivation of the heat did not occur until after the price event started). During the critical price period hot water is utilized by the homeowner which would in normal operations force a transition to electric mode.

However, as the minimum threshold for electric heat within the optimization is 90F, only heat pump is activated as the temperature falls below the 120F threshold for heat pump activation. This inherently saves energy and reduces homeowner costs.

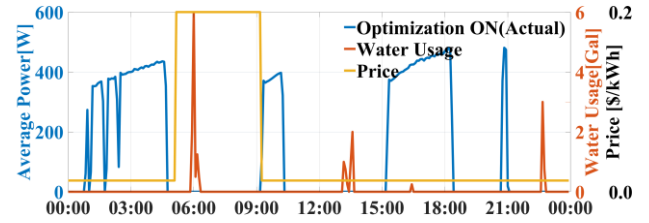


Fig. 9. Measured water heater demand from a single home

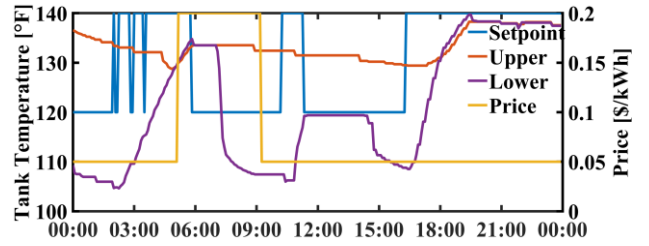


Fig. 10. Measured water heater temperature. from a single home

### 4) Single water heater measured results compared to simulation

Fig. 11 shows another home during the optimization off week. While the heat pump mode is only engaged to reduce consumption, this consumption occurs during the critical price period due to the utilization of hot water. Simulation shows that by preheating the water heater, the high price period can be completely avoided. Results of an economic comparison are shown in Table VII.

### 5) Neighborhood water heater measured results compared to simulation

Fig. 12 compares the hot water consumption versus simulated results and water utilization for the entire neighborhood. The hot water utilization is significant during the critical price period spurring a slightly delayed electrical consumption from many of the water heaters (as energy efficiency modes do not provide significant buffer before activating electric modes). As demonstrated in simulation, performing preheating through MPC leads to lower consumption during the critical price period.

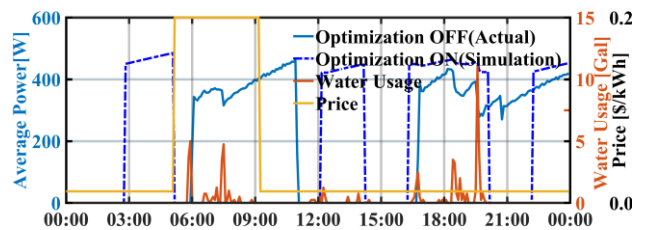


Fig. 11. Comparison of water heater optimization OFF with simulation of it ON for a real home

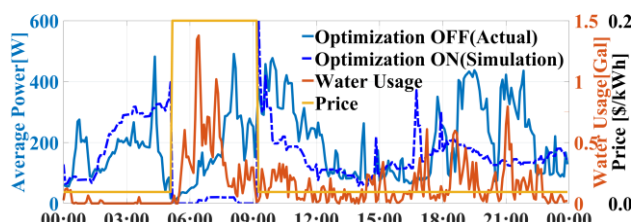


Fig. 12. Comparison of the measure average neighborhood water heater demand with optimization ON for some home with and a simulation of all homes with optimization ON

## VI. CONCLUSION AND LESSONS LEARNED

This paper presents a scalable MAS for optimizing and controlling residential building HVAC and water heater systems. This system allows for the shifting energy use from critical periods, through a dynamic price profile, without direct control from a utility. Data from an implementation project is presented to validate that the system does shift energy consumption from critical price periods.

From this work, water heaters represent a much better thermal storage medium as the allowable temperature range is much more significant. The 2F range of operating for the HVAC does not allow significant opportunity to store energy.

As presented, coordinated control of these system under a common shared incentive can lead to challenges associated with similar system responses. Initially, this was not anticipated as the diversity of operating conditions, different household behavior, hot water use patterns, HVCA temperature setpoint was expected to create a wide variety of responses. Furthermore, rebound and precooling in coordination could potentially lead to high load consumptions before and after high price period events.

In a real-world implementation, there are challenges that reduce potential benefits of full-scale utilization of the thermal inertia of the residential building and water heaters. These challenges include: interfacing with device APIs where the manufacturers updated the content and/or format of the data leading to breaks in the system; maximum allowable calls to the vendor APIs set to once every 5 minutes resulting in slow control and latency challenges; recurring connectivity issues caused by either the homeowners' wi-fi routers or device manufacturer's servers being offline; and homeowners electing to manually override their devices rather than changing their programmed setpoints and device point control limitations set by the manufacturer due to thermostat complexity.

In many cases, homeowners did not fancy their self-programmed schedules. After significant overriding challenges, control temperature limits have been imposed to restrict temperature alterations to only 1-2 degrees Fahrenheit. This restricted the potential storable energy within the residential building but resulted in fewer overrides. Reproducing the HVAC results in simulation under varying temperature thresholds (Fig. 13) indicates that during the desired time window HVAC demand can be reduced by almost 50% (8F  $\Delta T$ ) as oppose to just 9% (2F  $\Delta T$ ).

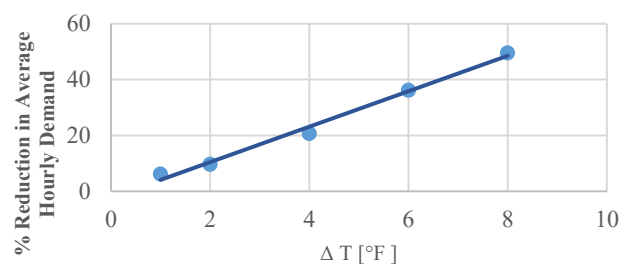


Fig. 13. Average annual percentage hourly HVAC demand reduction against optimization temperature band

As discussed, the long duration of the peak price event led to HVAC rebounds within the high price period. Simulations of varying high price periods, Fig. 14 Fig. 15, show that as the high price window increases the average reduction that can be expected in overall demand decreases. Hence, with this type of control short (several hour) high price periods will get the best result.

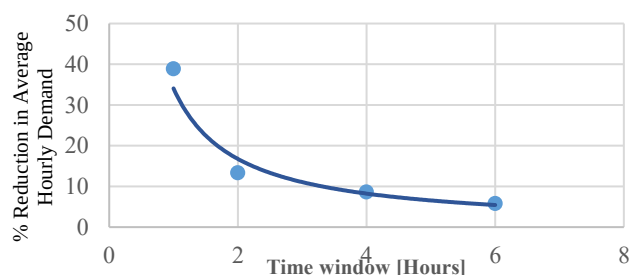


Fig. 14. HVAC demand reduction versus time windows for optimization

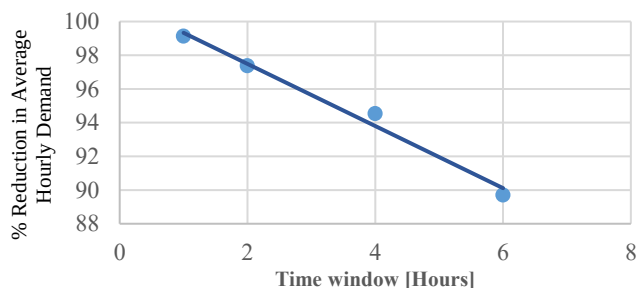


Fig. 15. Water heater demand reduction versus time windows for optimization

In future work, other approaches to incentivize behavior will be examined. In this work, only energy cost is considered and not demand. This allows for the optimization of the HVAC and water heater to be performed independently and by two separate agents. Demand management will require a different configuration of agents and communications.

Techniques for producing price signals which align individual and social optimality will also be explored. This will include techniques for producing price signals such as alternating direction method of multipliers (ADMM) which has been shown to work well in simulation done by the authors of [55].

## VII. ACKNOWLEDGEMENTS

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