A Real-time Agent Based Optimization and Control Approach for Residential Building Heating Ventilation and Air Conditioning Systems

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***Abstract*— The prevalence of the IoT (Internet of Things) is fostering the development of new control options and decision making that was not previously available. This is creating a wealth of opportunities for real-time control approaches and systems that can optimize for a common goal. This paper presents a smart residential neighborhood with optimization at the residential level utilizing a system of agents. The optimization utilizes information and modeling to optimize variable speed HVAC real-time operation in actual residential buildings. Data is presented showing the performance of the optimization and conclusions are drawn on next steps for development.**

***Index Terms*— control, HVAC, modeling, optimization, real-time**

α	solar absorptivity
a_{00} to a_{16}	HVAC performance coefficients
b_t^{off}, b_t^{cool}, b_t^{heat}	Binary representing HVAC is actively off, cooling or heating
C^{attic} C^{im}, C^{in} C^{w}	Thermal capacitance in the attic, mass, air and wall
C_{HVAC}	Maximum rated cooling capacity of HVAC
D_t^{HVAC}	Discomfort defined as delta indoor temperature excursion from operating range at time t
ΔT, t	Time step and time
h_{roof}, h_{wall}	convection coefficient roof and wall
I_{st}	Solar irradiance
L_2	Capacity loss coefficient (due to duct losses, etc.)
ρ_t	Price of electricity at time t
$P^{HVAC}{}_t$	Electrical power consumed by HVAC 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
Q_t^{min}	the HVAC system
Q_t^{IHL}	The heating associated with internal heat loads
T_t^{out}	Temperature of the outside
T_t^{attic}, T_t^{in}	Residential building attic, indoor, mass, and wall
T_t^{mass}, T_t^{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
$W_{P,}$ W_D	Weight factor associated with price and discomfort

I. Introduction

The IoT (Internet of Things) has produced a new generation of devices with accompanying systems which provide options for control and automatous decisions making. Although the focus has primarily been the convenience of the homeowner, they also present an opportunity for wider grid support as they can be used to help meet the reliability and efficiency needs of the grid through residential load management. Attempts to reap these benefits while preserving occupant comfort levels have been a challenge.

There are several methods which have been applied to the residential load control problem, and they fall into two broad categories, direct and indirect control. The first being governed at the utility level and the latter at the homeowner level via a Home Area Network (HAN) and motivated by incentives. Direct control strategies have been in use for decades as illustrated by [1]-[2], allowing utilities to switch off or limit demand from space conditioning loads by changing the temperature setpoint. Analysis has shown that peak reduction is achieved but at times at the expense of comfort [3]. Using homeowner preferences as the turn-on threshold [4] and model predictive forecasts [5] have been investigated to mitigating occupant discomfort. These approaches tend to require more information from the devices in the home which raises privacy concerns [6]. Thus, leading to the investigation of approaches which allow for the distribution of the optimization, by incorporation into the HAN.

Preheating and precooling are other options that have been evaluated for the purpose of shifting load in [3],[7],[8]. In the studies performed, the building's indoor temperature is raised or lowered (depending on the season) before a period of critical peak pricing and allowed to drift during that event. This is based on the implementation of a real-time price hike and self-control issued by the homeowner.

More complexed approaches are increasing in prevalence due to the advent of learning algorithms and the availability of data. In [9] an overview of the various approaches is given for both the individual home level and neighborhood level which is divided into 2 categories: centralized, being an extension of the individual home approaches, and distributed.

Multiple game-theory approaches are mentioned in [9], however [10] indicates that the cost functions usually necessary for them to work are not easily accessible to the homeowner and they do not have the complexity require to capitalize on the available energy storage potential. Mixed integer linear programing (MILP) by having representations for the status and consumption of devices allows for optimizing conflicting objectives even with uncertainty in the inputs [9].

The authors of [10] have shown there exists a time-varying price signal that produces this ideal situation. This time-varying price is such that when the homeowner selfishly optimizes based on it their individual optimality and social optimality align. Creating this price signal requires a forecast of the expected load and can be difficult without transactive capabilities.

Southern Company, Alabama Power, and Oak Ridge National Laboratory have partnered to establish a Smart Neighborhood™ project to look at control and optimization of residential loads to support the grid. In this paper, a representation of the optimization and controls strategies utilized to dispatch HVAC in real-time are presented. Measured results from the neighborhood are shown.

II. Background

In this project, a microgrid with sixty-two residences in a community has been constructed as shown in Fig. 1. While the residential homes are fitted with many advanced IoT devices, HVAC and water heating are the primary resources available for control and support of cost savings. HVAC is a prime candidate for controls as space heating and cooling typically comprise more than 45% of residential energy use [11].

Fig. 1. Birdseye view of the neighborhood. Source: Southern Company

An agent-based framework used to support HVAC optimization and control framework is shown in Fig. 2 [12]. The framework uses a price signal, weather forecasts, building model, and heat load prediction as inputs to an optimization. Included in the framework are agents responsible for communication with the HVAC vendor application programming interface (API) and procuring current status information and temperature data form the thermostat. The HVAC optimizer agent attempts to minimize electricity cost while maintaining occupant comfort. The optimization uses a model predictive control (MPC) formulation of an electrical equivalent model to represent the home.

Carrier Greenspeed variable speed heat pump [13] systems have been installed at each home. The variable speed functionality provides a range of cooling options but can be difficult to directly relate with MPC. In the following sections, the methodology for real-time optimization and control is presented.

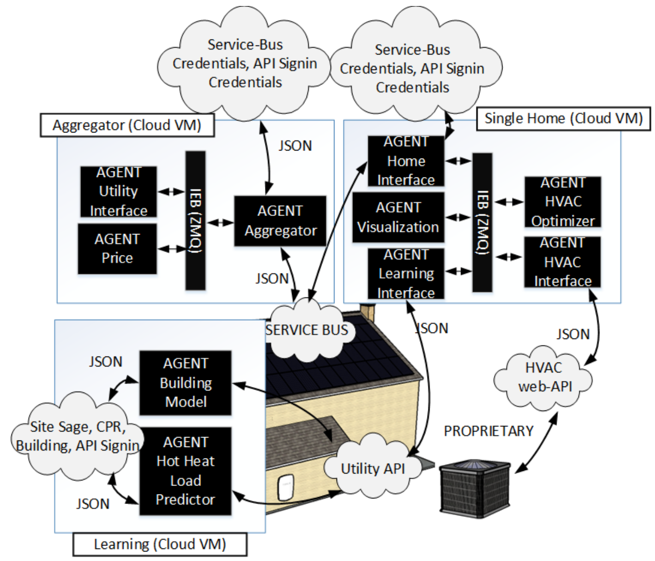

Fig. 2. Depiction of agent-based framework

III. Optimization

The primary objective of the optimization is to reduce the cost of purchased electricity on behalf of the homeowner while attempting to maintain comfort. To do this, the objective function considers both the cost of electricity and the impact of excursions outside the allowable temperature window of comfort specified by the homeowner. The detailed models of the building envelope, and HVAC model system form the optimization constraints and are discussed in the following sections.

A. Objective Function

The multi-objective optimization defined for the HVAC optimization and control can be written as (1) and is focused on both minimizing the effective discomfort and cost:

$$\min(W_P \sum_{t=0} P_t^{HVAC} \rho_t + W_D \sum_{t=0} D_t^{HVAC}) \qquad (1)$$

B. HVAC System Constraints

The HVAC optimization is composed of constraints capturing the thermal response of the building envelope, the HVAC system, and occupant comfort. The bounds of temperature operation are pulled directly from the HVAC thermostat which support scheduling of heating (T_{min}) and cooling (T_{max}).

Since, the indoor temperature may be outside the comfort range due to a setpoint or mode change issued by the homeowner, an auxiliary variable associated with discomfort has been added to the objective function. In this way, the optimization can successfully solve and drive the indoor temperature to the desired range quickly. A key component to this work is to ensure customer participation is not threatened by discomfort due to temperature excursions. This variable is constrained by the following equations (2)-(4):

$$D_t^{HVAC} \geq T_t^{in} - T_t^{max} \tag{2}$$

$$D_t^{HVAC} \geq T_t^{min} - T_t^{in} \tag{3}$$

$$D_t^{HVAC} \geq 0 \tag{4}$$

The residential building has been modeled by an electrical equivalent system as shown in Fig. 3 [14] and validated in [15].

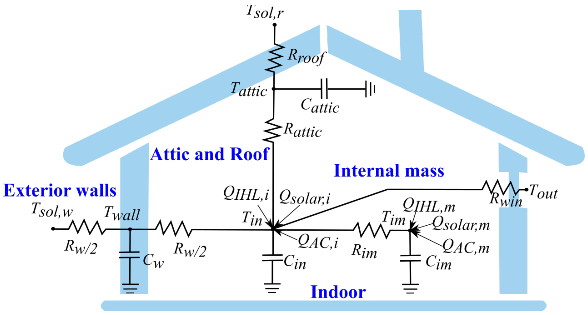

Fig. 3. Electrical model representation of residential building.

This model represents the thermal state of the building using four equations to calculate the indoor air temperature, indoor thermal mass temperature, exterior wall temperature, and attic temperature for the next timestep. The equations are coupled by the heat transfer between the temperature nodes and include heat transfer due to outdoor temperature and solar irradiance. The temperature nodes outside the building *Tsol,w(t)* and *Tsol,r(t)* can be calculated using forecast data of outdoor temperature data and solar irradiance as shown in (5) and (6):

$$T_t^{sol,w} = T_t^{out} + I_{st} \times \frac{\alpha_{wall}}{h_{wall}} \tag{5}$$

$$T_t^{sol,r} = T_t^{out} + I_{st} \times \frac{\alpha_{roof}}{h_{roof}} \tag{6}$$

From the electrical network above, the wall temperature can be represented by (7):

$$T_{t+1}^{wall} = \left(\frac{T_t^{sol,w} - T_t^{wall}}{\frac{R_W}{2}} + \frac{T_t^{in} - T_t^{wall}}{\frac{R_W}{2}} \right) \times \frac{\Delta t}{C_W} + T_t^{wall} \tag{7}$$

The attic temperature can be represented by (8):

$$T_{t+1}^{attic} = \left(\frac{T_t^{in} - T_t^{attic}}{R_{attic}} + \frac{T_t^{sol,r} - T_t^{attic}}{R_{roof}} \right) \times \frac{\Delta t}{C_{attic}} + T_t^{attic} \tag{8}$$

The mass temperature can be represented by (9):

$$T_{t+1}^{mass} = \left(\frac{T_t^{in} - T_t^{mass}}{R_{im}} \right) \times \frac{\Delta t}{C_{im}} + T_t^{mass} \tag{9}$$

Finally, the indoor temperature can be represented by (10):

$$T_{t+1}^{in} = \left(\frac{T_t^{wall} - T_t^{in}}{\frac{R_W}{2}} + \frac{T_t^{attic} - T_t^{in}}{R_{attic}} + \frac{T_t^{mass} - T_t^{in}}{R_{im}} + \frac{T_t^{out} - T_t^{in}}{R_{win}} + L_2\, Q_t^{air} \right) \times \frac{\Delta t}{C_{in}} + T_t^{in} \tag{10}$$

The initial conditions for the equations are based on available measurements within the building and other data. The indoor temperature $T_{in}(0)$ is the measured temperature at the thermostat, $T_{mass}(0)$ is assumed to be equal to $T_{in}(0)$, $T_{wall}(0)$ is assumed to be halfway between the indoor and $T_{sol,w}(0)$, and the $T_{attic}(0)$ is assumed to approximately equal to the $T_{sol,r}(0)$.

Since the HVAC system is a variable speed unit, the cooling and heating capacity are not a fixed value actuated by a binary off and on, but instead fall within a range given by both sensible heating and cooling as shown in (11):

$$Q_t^{min} \leq Q_t^{cool} \leq Q_t^{max} \tag{11}$$

Since the solver is linear, the maximum and minimum sensible cooling constraints of the HVAC system were determined based on indoor temperature and a constant associated with a sixth order best-fit linked to the outdoor temperature. The equations (12) and (13): represent the maximum and minimum cooling capacity. The corresponding heating capacity equations are of the same form

$$Q_t^{max} = a_{00} + a_{01}T_t^{out} + a_{02}{T_t^{out}}^2 + a_{03}{T_t^{out}}^3 + a_{04}{T_t^{out}}^4 + a_{05}{T_t^{out}}^5 + a_{06}{T_t^{out}}^6 \tag{12}$$

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

Simply setting the constraints as shown in (11) does not obtain the expected results as cooling capacity can be zero when the HVAC is off. Five equations are used to bind the cooling capacity and five for the heating capacity within the operational space of the variable speed operation for optimization (14)-(18) and (19)-(23) respectively.

Cool Mode Only:

$$Q_t^{heat} = 0 \tag{14}$$

Cool Mode and Auto:

$$Q_t^{cool} \leq Q_t^{max}\, b_t^{cool} \tag{15}$$

$$Q_t^{cool} \geq Q_t^{min} - Q_t^{min}\, b_t^{cooloff} \tag{16}$$

$$Q_t^{cool} \geq 0 \tag{17}$$

$$b_t^{cool} + b_t^{cooloff} \leq 1 \tag{18}$$

Heat Mode Only:

$$Q_t^{cool} = 0 \tag{19}$$

Heat Mode and Auto:

$$Q_t^{heat} \le Q_t^{max}\, b_t^{heat} \quad (20)$$

$$Q_t^{heat} \ge Q_t^{min} - Q_t^{min}\, b_t^{heatoff} \quad (21)$$

$$Q_t^{heat} \ge 0 \quad (22)$$

$$b_t^{heat} + b_t^{heatoff} \le 1 \quad (23)$$

Off:

$$Q_t^{cool} = 0$$

$$Q_t^{heat} = 0$$

To ensure that the optimization does not try and put the HVAC in both cooling and heating mode and allow for an off-state, a binary set of variables as follows were defined (24):

$$b_t^{cool} + b_t^{heat} + b_t^{off} \le 1 \quad (24)$$

The sensible cooling and heating are combined into a single variable to allow for heating or cooling as follows (25):

$$Q_t^{air} = Q_t^{heat} - Q_t^{cool} \quad (25)$$

The cooling and heating outputs are linked back to the electrical consumption using a coefficient of performance COP. Finally, the electric consumption by the HVAC system is defined as (26) for heating and (27) for cooling:

For Heating:

$$P_t^{HVAC} = \left(P_t^{minheat}\, b_t^{heat} + P_t^{maxheat}\right) - \left(P_t^{minheat} \times \frac{Q_t^{heat} - Q_t^{minheat} b_t^{heat}}{Q_t^{maxheat}}\right) \quad (26)$$

For Cooling:

$$P_t^{HVAC} = \left(P_t^{mincool}\, b_t^{cool} + P_t^{maxcool}\right) - \left(P_t^{mincool} \times \frac{Q_t^{cool} - Q_t^{mincool} b_t^{cool}}{Q_t^{maxcool}}\right) \quad (27)$$

For Off

$$P_t^{HVAC} = 0 \quad (28)$$

IV. Control

The control of the HVAC system requires an adaption of the optimization results. While the optimization considers a building model to perform the optimization and calculates the corresponding heating and cooling (power), they are not direct inputs to the HVAC. Instead, the HVAC system utilizes temperature setpoint control as direct control input. Hence, equivalencies were created to control the HVAC in relation to the optimization results and are discussed in the following sections.

A. *Control of HVAC System*

Among the outputs of the optimization is the expected indoor temperature and the sensible heating or cooling. Having the HVAC system dispatch directly the heating or cooling capacity based on the optimization would be ideal and be the most direct approach. However, the controllable options are Mode of Operation (auto/heat/cool/fan/off), T setpoint heat and T setpoint cool (both in half degree increments, Fahrenheit), and Fan on/off mode (which is typical of most residential controllable HVAC systems). Hence, correlations between the operation of the HVAC system in respect to the measured HVAC temperature were developed based on early indications of system behavior.

HVAC systems in general utilize a local measured temperature as a reference to make decisions based on temperature setpoint request. For the variable speed system, the differences in separation between the setpoint and measured temperatures lead to ranges as output cooling and heating as shown in Table I.

TABLE I. Adjustment of Tset to obtain wanted control.

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

The result of the optimization for the next 5 minutes is used to determine how to set the HVAC system to achieve the desired effect. This is compared to the measured indoor temperature directly at the thermostat and used to drive the HVAC system to the desired capacity.

One additional aspect that was included was the case where no cooling was requested. The HVAC system is still left in cooling mode to reduce the potential impact of a communication failure and instead issues a setpoint above the current measured temperature and within the comfort range, while considering the thermostat deadband, to force the HVAC into standby.

V. Experimental

An aggregator virtual machine along with 62 other virtual machines, one for each home in the neighborhood, were used to run the optimization and control software [12]. The software was developed using open source tools including the linear programming interface PuLP [16] and COINsolver [17]. Dispatching of the HVAC was limited to the frequency stipulated by the HVAC manufacturer (no more than once every 5 minutes).

Real world HVAC performance data (24 hours with HVAC optimization ON and 24 hours with it OFF) for a single home is presented in Fig. 4 and Fig. 5. The MPC forces an increase in demand precooling the home shortly before the high price period. This provides an opportunity to reduce demand during the peak period. As recorded peak reduction was determined to be 15% for HVAC (Fig. 4) and 11% for the entire home, (Fig. 5) during the high price period. Thermostat readings per zone are presented in Fig. 6. Precooling was limited to 2°F per zone to reduce impact on the homeowner. As shown, each zone is precooled to the minimum allowed temperature based on the schedule.

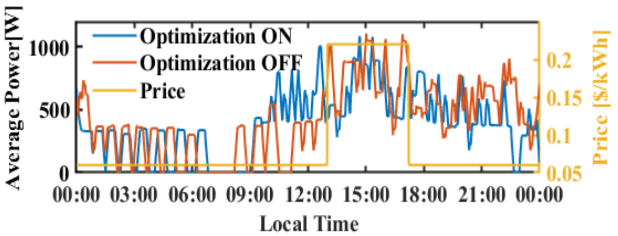

Fig. 4 Sample home HVAC demand profile for consecutive days one with optimization ON and the other with it OFF with price signal superimposed

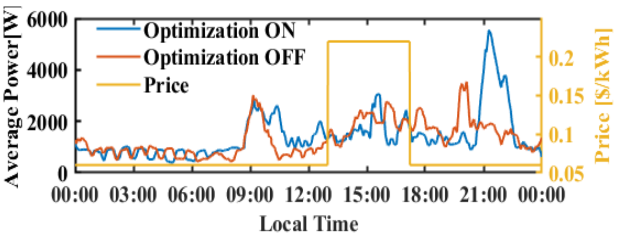

Fig. 5 The total demand for a sample home for 2 for consecutive days one with HVAC optimization ON and the other with it OFF with price signal superimposed

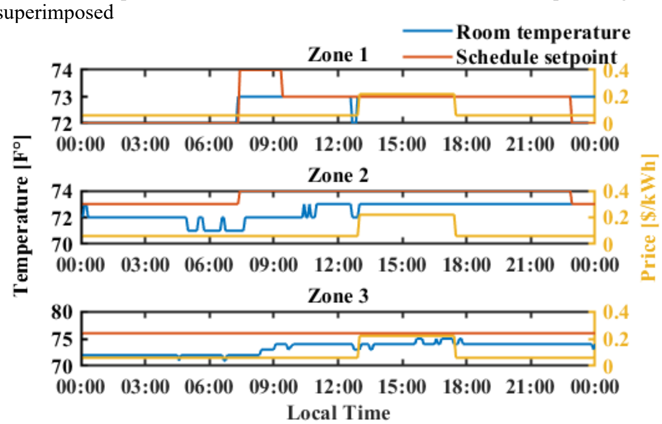

Fig. 6 HVAC setpoint schedules with measured indoor temperatures for the 3 zone of a single home and price signal superimposed

VI. Encountered Challenges

Challenges were encountered in implementation of the optimization and control strategies. The use of a variable capacity HVAC system while increasing efficiency produced a more complicated formulation of the MPC. Device manufacturers updated API content, sometimes quarterly, creating new formats of data and forcing software changes and lost opportunities. API calls were limited by the manufacturers to no more than once every 5 minutes causing significant roundtrip time in the MPC. A majority of homeowners choose to use manual control instead of schedules creating challenges with the MPC formulation. The thermostat setpoints were also limited to integer values.

VII. Conclusion

This paper presents a real-time optimization and control approach for variable speed HVAC in a distributed control architecture [12]. This presented optimization and control has been deployed in a real neighborhood. The results presented show an example HVAC demand profile and demonstrate that precooling a home to support peak reduction is feasible but has many challenges in actual deployment.

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