Implementation of the Distributed Resource AGGregation (dragg) Algorithm for Residential Buildings

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ABSTRACT

In this paper, a distributed resource aggregation algorithm is demonstrated for twenty homes. The algorithm relies on an aggregator to limit aggregate demand across individual homes, each solving a model predictive control optimization problem, using a reward price mechanism. Previous work has demonstrated this by modeling the home, HVAC system and water heater system. Here, we enable a larger variety of building configurations to exist by enabling PV, a battery, or both to be added to homes. The models are validated and the algorithm is analyzed across multiple prediction horizons and with different convergence limits. The algorithm proves effective in reducing the aggregate demand from 147 kW (no aggregator oversight) to 110 kW (with aggregator oversight).

1. INTRODUCTION

Grid-interactive Efficient Buildings (GEB) are defined as buildings with efficient energy consumption and demand flexibility [9], meaning that they are able to shift load in order to provide grid services. GEBs have attracted significant attention and investment recently from utilities and the U.S. Department of Energy (DOE) Building Technologies Office (BTO) due to their significant potential to offset load and delay or eliminate the need for utilities to invest in electrical generation assets by using demand side management techniques.

While the GEB landscape consists of many disciplines, one of particular interest is Model Predictive Control (MPC) applied to buildings. MPC is a useful methodology for providing grid services by optimizing aspects of building performance (energy consumption, peak demand, carbon emissions, etc.) while also adhering to time sensitive constraints. Significant work has been undertaken for formulating MPC in industrial, commercial, and residential buildings, and the authors refer to [11] as a recent, comprehensive overview of MPC in buildings. The rest of this paper will focus on MPC in residential contexts.

For residential building MPC, two important considerations include:

- How the residential building is to be modeled and exactly which aspects of the building will be considered. This includes the type of modeling formulation (white-box, grey-box, black-box), as well as which systems are included (HVAC system, hot-water heater, appliances, etc.)
- The objectives of the optimization to be performed. In the case of multi-objective optimization, the weighting approach of the different objectives is also important.

These considerations are discussed using a select number of example projects in the next few paragraphs.

In [5], a multi-objective MPC is formulated with respect to energy cost, thermal comfort, user convenience, and carbon emissions. Simplified white-box models are created to represent the PV system, battery system, hot water heater, dishwasher, and clothes dryer. A multi-parameter linear regression model is created with the same general formulation to represent each home / HVAC system using data from the Residential Building Stock Assessment (RBSA) [7]. Model parameters for each of the five homes modeled are trained using data (two weeks training, one-week validation) from different homes from the RBSA. The MPC is decentralized, as each home is optimized in isolation.

In [3], a typical home from the Pecan Street, Inc. smart grid demonstration project located in Austin, Texas is used for MPC. The authors build a full-scale energy model in EnergyPlus / OpenStudio they parametrically alter one of the thermostat set point, dry bulb temperature, or relative humidity at each hour to generate training and validation sets. These data sets are then utilized to train a polynomial regression model with interactive effects for predicting energy consumption of the whole home at the next time step. This simplified black-box model is then utilized in the MPC formulation, which is optimized with respect to energy consumption only. Energy costs utilize time-of-use (TOU) rates from the Austin load zone of the Electric Reliability Council of Texas (ERCOT) grid. The MPC for this problem is also decentralized.

The MPC formulation in [6] utilizes a grey-box model for both a home / HVAC system model and a water heater, with both models formulated using resistance capacitance (RC) parameters. The objective function is formulated with respect to the energy cost and thermal comfort (via a discomfort index). In contrast to [3,5], however, the authors design a centralized aggregator that is responsible for maintaining compliance with a demand response (DR) signal across a collection of homes aggregated at a feeder level. This is accomplished by manipulating the energy cost in an iterative fashion for all homes via a DR reward price, such as to influence the control behavior of each home until the aggregate demand of homes meets the requirements of the aggregator. Models for the water heater and home / HVAC system are generated by sampling uniform distributions of RC parameters.

To summarize, the formulation of the model(s) and objective function in MPC can vary significantly. Multiple models can be constructed separately for different systems within a residential building via simplified white-box and black-box techniques from real data-sets then aggregated [5]; physics based simulations can be used to generate significant amounts of data, which is used to construct a single, highly accurate black-box model [3]; grey-box models can be used to construct systems within homes for aggregation [6]; MPC can be formulated for individual homes or an aggregate of homes.

The research presented in this paper will adopt the following from [6]:

- The residential building owner (RBO) optimization and aggregator calculation will be used
- The HVAC and water heater model will be used
- The optimization will be designed to minimize energy cost at the RBO level, but will not consider the discomfort index

- The aggregator will iterate with the individual RBO optimization in order to meet a DR threshold

In addition, the research will incorporate aspects of [5] to understand how the additional systems affect the ability of homes to reduce costs:

- Addition of a PV system model
- Addition of a battery system model

Construction of the detailed energy model and extensive number of data sets in [3], while creating a highly accurate black-box model ($R^2 = 0.986$), is seen as overly burdensome and suffers from many of the traditional shortcomings of MPC. The only aspect incorporated into this study is the TOU rates.

Moreover, the research will produce a Python toolbox[1] which utilizes the CVXPY library for optimization [4]. The intention of the toolbox will enable users to:

- Define a uniform distribution of RC parameters for the water heater and HVAC model, along with the power consumption of the two appliances
- Define battery charging rates, capacity, and efficiency
- Define PV system areas and efficiencies
- Define the total number of homes considered by the aggregator, as well as the proportion of homes that have PV and / or battery systems
- Define the TOU electricity profiles
- Define the prediction horizon used in the MPC

The remainder of the paper is organized as follows. Section 2 summarizes the RBO and aggregation methodologies from [6]; Section 3 discusses the mathematical formulation of the different system models and objective function utilized in the MPC; Section 4 describes the specific experiment setup used in this analysis; and Section 5 presents results and Section 6 concludes.

2. Distributed Formulation

One of the key interesting challenges undertaken in [6] is the formulation of the problem as a distributed MPC exercise with aggregator oversight. This is designed to mimic real interactions between individual RBOs and a third-party entity.

Key to this approach are the two layers, the RBO and the load aggregator, which work in tandem to optimize home operations as well as meet maximum demand limits. The aggregator uses a reward price (RP) to drive electrical consumption down at times where individual behavior would exceed maximum desired demand thresholds. The nature of the relationship is displayed in Figure 1.

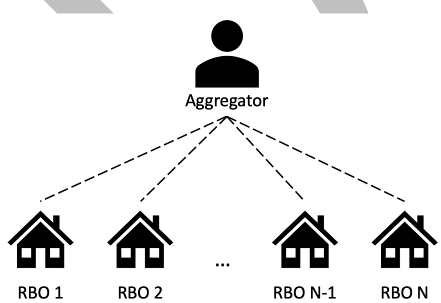

Figure 1 Aggregator and RBO coordination, adapted from [6]

2.1 Residential Building Owner

Each RBO operates their home independently of one another, meaning that the MPC problem is solved for each RBO in isolation. A Home Energy Management System (HEMS) is dedicated to the coordination and optimization of the individual systems for each RBO, which then interacts directly with the aggregator. The single objective optimization problem solved for by each HEMS at time t is:

$$min \sum (c_i^t - r^t) \cdot P_{grid_i}^t, \forall i \tag{1}$$

where α and β are weighting factors associated with the RBOs discomfort index and modified energy cost, Dis_i^t is the thermal discomfort factor of home i at time t, c^t is the cost of electricity at time t, r^t is the RP at time t, and $D_{gr_i}^t$ is the aggregated load of home i at time t. For the remainder of the paper, $(c^t - r^t) \cdot D_{gr_i}^t$ is referred to as the modified energy cost and $c^t \cdot D_{gr_i}^t$ is referred to as the unmodified energy cost.

After each HEMS solves their MPC problem, their expected demand at the next time interval (t) is sent to the aggregator. The HEMS then waits for a response from the aggregator. The response is either:

- Proceed as calculated.
- Re-implement optimization given an updated RP parameter

2.2 Aggregator

The role of the aggregator is to ensure that the sum of demand from all individual homes under its purview is less than a critical threshold:

$$\sum_{i=0}^{N} P_{grid_i}^t \leq D_{max}^t \tag{2}$$

where N is the total number of homes considered by the aggregator, $P_{grid_i}^t$ is the demand experienced by the grid from house i at time t, and D_{max}^t is the maximum demand threshold imposed by the aggregator. In real-life deployment scenarios, D_{max}^t could be imposed by a centralized operator, could be designed to maintain safe operation of the distribution equipment, or could be a time varying combination of both depending on the overall needs of the grid.

In order to influence energy consumption, the aggregator and HEMS utilize the RP, which is basically a modification factor to the electricity cost. The RP is always a negative value, so when subtracted from the electricity cost in (1), it ends up increasing the modified energy cost. At the beginning of every time step and the zeroth iteration, as displayed in (3), the RP imposed by the aggregator is reset to zero such that the modified and unmodified energy costs are equivalent. Based on the aggregate demand, the RP is either modified or left unmodified. This is described by the following equations:

$$r^0 = 0 \tag{3}$$

$$D_{agg}^t = \sum_{i=0}^{N} P_{grid_i}^t \tag{4}$$

$$D_{mar}^t = \max\left(D_{max}^t - D_{agg}^t, 0\right) \tag{5}$$

$$r^{iter} = r^{iter-1} + D_{mar}^t \cdot \varepsilon \tag{6}$$

where r^{iter} is the RP at the $iter$th iteration, D_{mar}^t is the marginal load at time t and will always be less than or equal to zero, and ε is

[1] The tool is available at https://github.com/corymosiman12/dragg

the step size coefficient. Note that the iteration will only proceed if $D_{mar}^{t} < 0$. Based on results presented in [6], ε=1e-7 will be used throughout this paper.

In summary, the sequence of steps taken by the aggregator in order to satisfy (2) at every timestep t are as follows:

1. Set the reward price for the zeroth iteration.
2. Wait for all HEMS to solve the MPC optimization and report back expected demand.
3. Check if the expected demand is greater than the maximum allowable demand.
4. If true, modify the RP, rebroadcast to all HEMS, and repeat starting from step 2.
5. If false, conclude the calculation for that time step and proceed to the next time step.

3. Model Formulation

This section describes the mathematical formulation for the different system models used, as well as the constraints imposed on the system models.

3.1 Home HVAC System

The home and HVAC system used are presented as a coupled RC model as follows, as presented in [6], the only difference being that both heating and cooling are considered:

$$T_{in_i}^{t} = T_{in_i}^{t-1} + \frac{\left[\frac{\left(T_{out_i}^{t} - T_{in_i}^{t-1}\right)}{R_{house_i}} - S_{cool_i}^{t} \cdot P_{cool_i} + S_{heat_i}^{t} \cdot P_{heat_i}\right] \cdot \Delta \mathrm{t}}{C_{house_i}} \tag{7}$$

where $T_{in_i}^{t}$ is the indoor air temperature in the ith home at time t, $T_{in_i}^{t-1}$ is the indoor air temperature in the ith home at the previous time step, $T_{out_i}^{t}$ is the outdoor air temperature at time t, $S_{cool_i}^{t}$ and $S_{heat_i}^{t}$ are binary variables representing the operating status of the cooling and heating system in house i at time t, P_{cool_i} and P_{heat_i} are the power rating of the cooling and heating system of house i, R_{house_i} is the thermal resistance of house i, C_{house_i} is the thermal capacitance of house i, and Δt is the time step. The heating system is intended to represent electric resistance heating, with a 100% efficiency. The cooling system, however, is highly simplified and does not consider efficiency, nor that the efficiency for direct-expansion systems are dependent on temperature differentials.

The constraints imposed on the home and HVAC system model include staying within temperature bounds and the binary nature of the operating status for the heating and cooling system:

$$S_{cool_i}^{t}, S_{heat_i}^{t} \in \{0,1\} \tag{8}$$

$$T_{in,min} \leq T_{in_i}^{t} \leq T_{in,max} \tag{9}$$

where $T_{in,min}$ is the lower bound on the indoor air temperature and $T_{in,max}$ is the upper bound on the indoor air temperature.

3.2 Water Heater System

The water heater system is also coupled with the indoor air temperature, as the temperature difference between the indoor air and water in the tank drives heat loss from this system. It is similar to the home HVAC system model, also as presented by [6]:

$$T_{wh_i}^{t} = T_{wh_i}^{t-1} + \frac{\left[\frac{\left(T_{in_i}^{t} - T_{wh_i}^{t-1}\right)}{R_{wh_i}} + S_{wh_i}^{t} \cdot P_{wh_i}\right] \cdot \Delta \mathrm{t}}{C_{wh_i}} \tag{10}$$

where $T_{wh_i}^{t}$ is the water heater temperature in the ith home at time t, $T_{wh_i}^{t-1}$ is the water heater temperature in the ith home at the previous timestep, $S_{wh_i}^{t}$ is a binary variable representing the operating status of the water heater in house i at time t, P_{wh_i} is the power rating of the water heater of house i, R_{wh_i} is the thermal resistance of the water heater in house i, and C_{wh_i} is the thermal capacitance of the water heater in house i. This water heating system is also meant to represent an electric resistance heating system with 100% efficiency. Similar to the home and HVAC system, the constraints include:

$$S_{wh_i}^{t} \in \{0,1\} \tag{11}$$

$$T_{wh,min} \leq T_{wh_i}^{t} \leq T_{wh,max} \tag{12}$$

3.3 Battery System

The battery system model is taken verbatim from [5]:

$$E_{b_i}^{t} = E_{b_i}^{t-1} + \Delta \mathrm{t}\left[\eta_{\mathrm{ch}_i} \cdot P_{ch_i}^{t-1} + \frac{P_{dis_i}^{t-1}}{\eta_{\mathrm{dis}_i}}\right] \tag{13}$$

where $E_{b_i}^{t}$ is the state of charge of the battery in house i at time t, $E_{b_i}^{t-1}$ is the state of charge of the battery in house i at the previous time step, η_{ch_i} and η_{dis_i} are the charging and discharging efficiencies of the battery in home i, E_{cap_i} is the battery capacity of home i, $P_{ch_i}^{t-1}$ and $P_{dis_i}^{t-1}$ are the charging and discharging power of the battery in home i. The following constraints are imposed on the battery system:

$$E_{b,min_i} \leq E_{b_i}^{t} \leq E_{b,max_i} \tag{14}$$

$$-P_{ch_i}^{t-1} \leq 0 \tag{15}$$

$$P_{dis_i}^{t-1} \leq 0 \tag{16}$$

$$P_{dis_i}^{t-1} \cdot P_{ch_i}^{t-1} = 0 \tag{17}$$

$$-P_{dis_i}^{t-1} \leq P_{b,max} \tag{18}$$

$$P_{ch_i}^{t-1} \leq P_{b,max} \tag{19}$$

where E_{b,min_i} and E_{b,max_i} are the lower and upper bounds on the battery state of charge (both of which are a percentage of the battery capacity, E_{cap_i}), (14) ensures the actual battery state of charge remains between these bounds, (15) defines battery charging as positive, (16) defines battery discharging as negative, (17) ensures that the battery is either charging or discharging but not both for any given timestep, and (18), (19) ensure the charging and discharging rates are below a threshold, $P_{b,max}$. As performed in [5], since battery back-feeding is undesirable due to round trip losses, the additional constraint is defined to ensure power discharged by the battery is consumed behind the meter:

$$P_{load_i}^{t-1} + P_{ch_i}^{t-1} - P_{dis_i}^{t-1} \geq 0 \tag{20}$$

3.4 PV System

The model used for the PV system is a simple model as presented in [2]:

$$P_{pv_i}^{\ t} = P_{GHI}^{t} \cdot A_{pv_i} \cdot \eta_{pv_i}(1 - U_{pv_i}^{t}) \tag{21}$$

where $P_{pv_i}^{\ t}$ is the power produced by the PV system of house i at time t, P_{GHI}^{t} is the global horizontal irradiance at time t, A_{pv_i} is the

PV system area for house i, η_{pv_i} is the PV system efficiency of house i, and $U_{pv_i}^t$ is the percent curtailment of the PV system. The power produced by the PV system is considered positive – this will be accounted for in the overall power balance equation. The constraint placed on the PV system ensures that the curtailment is a continuous variable between 0 and 1, with zero representing no curtailment and 1 representing 100% curtailment:

$$0 \leq U_{pv_i}^t \leq 1 \tag{22}$$

3.5 Other Constraints

The total home load and the overall power balance are described by the following:

$$P_{load_i}^t = P_{cool_i} \cdot S_{cool_i}^t + P_{heat_i} \cdot S_{heat_i}^t + P_{wh_i} \cdot S_{wh_i}^t + \tag{23}$$

$$P_{grid_i}^t = P_{load_i}^t + P_{ch_i}^t + P_{dis_i}^t - P_{pv_i}^t \tag{24}$$

where $P_{load_i}^t$ is the load of home i at time t which must be met through a combination of battery discharging, PV output, or power supplied by the grid, and $P_{grid_i}^t$ is the net demand experienced by the grid from house i at time t.

4. Experiment Design

The experiment utilizes variation in the resistance and capacitance values for the homes and the water heater to provide variation amongst the population, which are sampled from uniform distributions, as described in [6]. Furthermore, the toolbox enables four different home types to be declared. All homes have an HVAC and water heater system, however, homes can be declared to also have PV, a battery, or both. Full configuration for the experiment is presented below.

Table 1 Experiment Details[2]

Parameter	Value	Units
Total Homes	20	
Battery Only Homes	4	
PV Only Homes	4	
Battery & PV Homes	4	
Base Homes	8	
R_{house_i}	U[6.8, 9.2]	kWh/K
C_{house_i}	U[4.25, 5.75]	K/kW
P_{cool_i}, P_{heat_i}	3.5	kW
R_{wh_i}	U[18.7, 25.3]	kWh/K
C_{house_i}	U[4.25, 5.75]	K/kW
P_{wh_i}	2.5	kW
$P_{b,max}$	5	kW
Battery Limits	15%, 85%	
E_{cap_i}	13.5	kWh
$\eta_{ch_i}, \eta_{dis_i}$	0.95, 0.99	
A_{pv_i} [8]	32	m2
η_{pv_i}	0.20	
$T_{in_i}^0, T_{wh_i}^0$	19.3, 45.75	C
$T_{in,min}^t, T_{in,max}^t$	19, 21	C
$T_{wh,min}^t, T_{wh,max}^t$	45.5, 48.5	C
ε	5e-5	
Max Load Threshold	0.9	
Start	2015-01-01 00	
End	2015-01-02 00	
Random Seed[3]	12	

In order to maintain consistency with respect to the parameters of the individual homes and systems within the homes, the parameter selection process was performed prior to any of the scenarios being run. The experiment is performed using Houston data for irradiance and outdoor temperature as downloaded from the National Solar Radiation Database (NSRDB) [10]. Hourly energy prices are extracted from the ERCOT historical day ahead market for the Houston load zone (LZ_HOUSTON) [12].

The experiment is designed to run in two stages. The first stage runs MPC for all of the homes in isolation without oversight from an aggregator (referred to as RBO MPC). Prediction horizons of 1, 4, 6, 8, 10, and 12 hours are run. Using a prediction horizon of one enables business as usual type control, where the HVAC system or water heater system will run only to maintain setpoint (referred to as the baseline control). The purpose of this stage is to understand a) the expected behavior of the homes when they are all acting in a 'greedy' fashion without oversight, b) the time required to solve the MPC for the different time horizons, and c) the maximum expected demand given the population of homes. This maximum expected demand is then used to set the DR threshold (D_{max}^t) for use in the second stage of the experiment. The second stage (referred to as AGG MPC) uses the outcome of the first stage to run the same population of homes in accordance with the aggregator framework described earlier.

The entire problem is implemented in Python with the CVXPY library. Due to the binary nature of the heating, cooling, and water heating decision variables, the problem formulated is a mixed integer linear program, and therefore needed a different solver. The CVXOPT [1] package is used with the GLPK_MI solver.

5. Results

5.1 Validation of MPC Control

Validation of the expected control signals to ensure the home / HVAC models, water heater models, and battery models were behaving as expected was performed. The baseline control is shown below (Figure 2) for a multi-day scenario and performs as expected – a heating command is followed by an increase in indoor air temperature and setpoint is maintained.

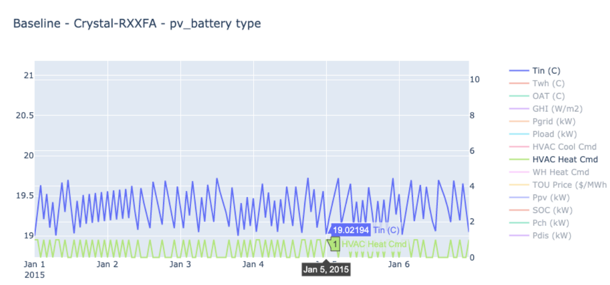

Figure 2 Baseline Home and HVAC System Control Validation

2 All experiment details are defined in the config.json file of the project Github page and easily modified for new experiments.

3 Given the same number of homes, this value will enable home names as well as parameters to be the same for exact reproducibility.

Similarly, visual validation for a water heater model is shown for a home using a prediction horizon of 10 hours (Figure 3), which also performs as expected. Finally, validation for the different loads in the home can be seen in Figure 4 using a prediction horizon of 4 hours, namely: the maximum state of charge never passes 11.475 kWh; the battery is never simultaneously charging and discharging (even though this wasn't directly imposed as a constraint, the solution still achieves this which makes sense); changes in battery state of charge always follow a one hour offset from when the battery is charging / discharging; and home load and grid demand is consistent with Equations (23) and (24).

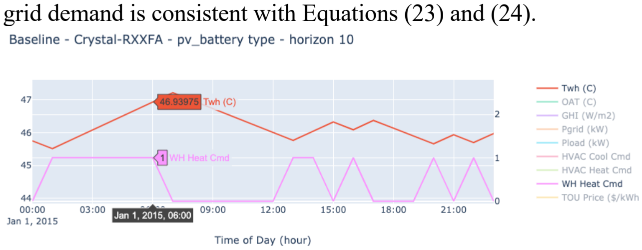

Figure 3 Water Heater System Validation - RBO MPC with 10 Hour Horizon

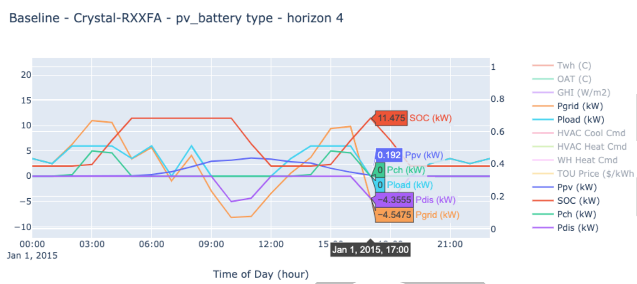

Figure 4 Validation of Power Balance and Battery Constraints – RBO MPC with 4 Hour Horizon

5.2 RBO MPC

For the RBO MPC only scenario, the homes behave in the expected greedy manner for all prediction horizons besides one (Figure 5), causing significant ramping and peaking in order to consume little electricity during peak pricing (5pm - 6pm). In the baseline scenario (horizon=1), the aggregate load profile is relatively flat.

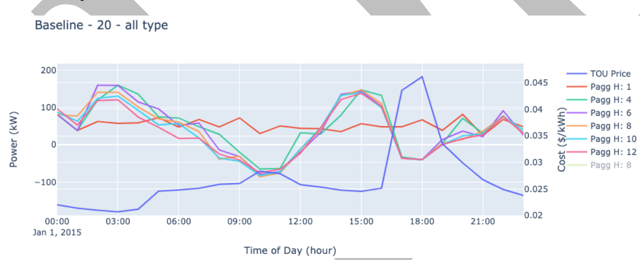

Figure 5 Aggregate load profiles during RBO MPC

Increases in peak aggregate demand (Table 2) are highly undesirable from the utility perspective. They would likely rather prefer the baseline case compared to any of the RBO MPC control strategies performed in isolation. The intention of imposing a DR limit through an aggregator entity is to allow bounded, communal optimization so as to benefit all parties involved (both utilities and individual homeowners).

Table 2 Maximum aggregate load, solve time, and aggregate cost for the 24-hour RBO MPC

Horizon	Pagg Max (kW)	Solve Time (s)	Aggregate Cost ($)
1	81.5	16	34.51
4	160	18	25.66
6	160	19	22.76
8	147	27	20.27
10	139	102	18.28
12	137	958	16.06

The time required for solving the MPC increases exponentially as the number of horizons increase[4], while the aggregate cost across all homes decreases relatively linearly with increased horizons. Based on these two factors, a prediction horizon of 8 was chosen for the AGG MPC implementation as a sensible medium between aggregate energy cost for all homes and computational expense.

5.3 AGG MPC

The smallest maximum demand achieved for the RBO MPC was 81.5 kW, so the main question of interest is to see whether or not the AGG MPC can achieve similar demand, while reducing aggregate cost. Initially, a demand limit of 85 kW was imposed, but the algorithm was unable to converge. The demand limit was increased to 115 kW where it was finally able to converge with a maximum aggregate load of 110 kW (a 20% decrease in max load over the RBO MPC with a horizon of 12). However, the fact that the baseline control scenario still outperforms all other scenarios is still seen as a discrepancy. It was attempted to overcome this discrepancy by modifying the value of the step size coefficient (ε), however, as shown in the following figures, a significant increase in iterations (160 for TS: 14) was required for the algorithm to converge, with no change in the actual settled reward price.

Figure 6 Aggregate Costs and Loads with ε = 5e-4

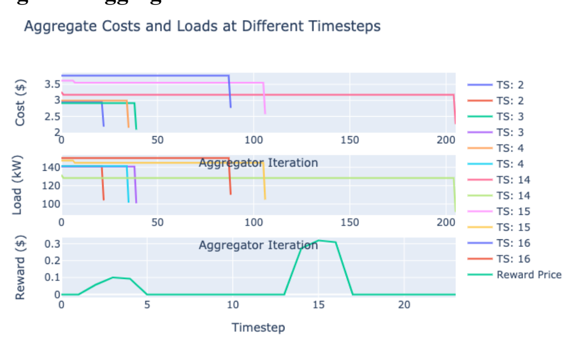

Figure 7 Aggregate Costs and Load with ε = 1e-4

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[4] The solve times were performed on a 2.9 GHz Intel Core i9 processor.

Moreover, with the current implementation of the algorithm, there are no minor step changes in grid load. The majority of the time, the only change in control strategy occurs for the battery only or PV and battery homes, which consists of changing the time that the battery is charged / discharged.

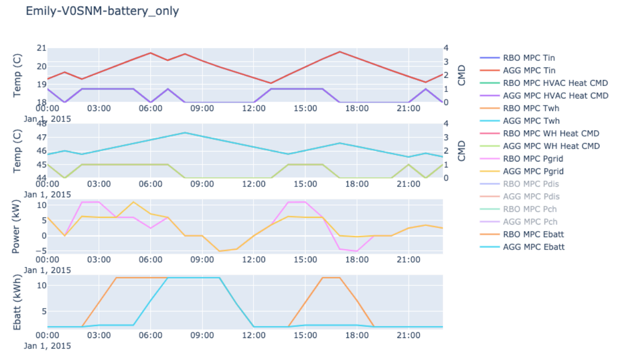

Figure 8 Comparison of Control for RBO MPC and AGG MPC for a Battery Only Home with an 8 Hour Horizon

Figure 8 displays the differences in charging patterns for a *battery only* home. Note that Tin and Twh, along with the control signals, for both the RBO MPC and AGG MPC are identical (they are perfectly overlaid and only one is visible).

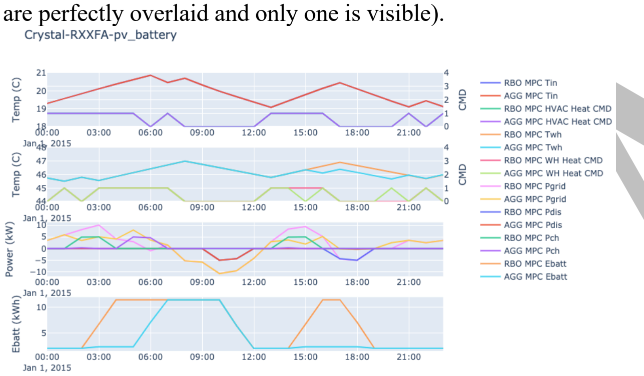

Figure 9 Comparison of Control for RBO MPC and AGG MPC for a PV and Battery Home with an 8 Hour Horizon

All of the *PV and battery* homes had differing control profiles for the battery control, however, the Crystal home (Figure 9) changed battery control along with water temperature heating control.

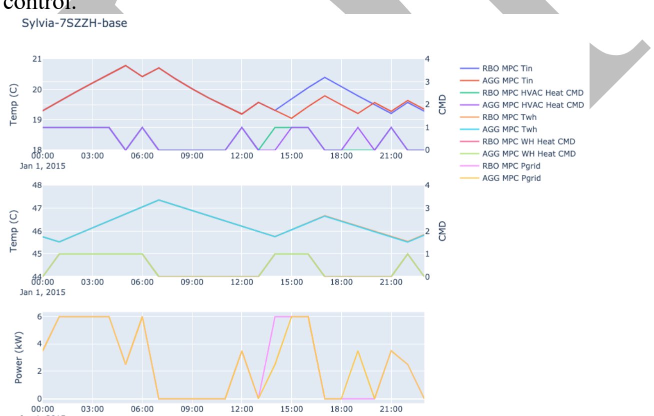

Figure 10 Comparison of Control for RBO MPC and AGG MPC for a Base Home with an 8 Hour Horizon

The only *base* home to change behavior between the RBO and AGG scenarios is the Sylvia home, which forewent heating at 2pm in the AGG MPC scenario (Figure 10). None of the *PV only* homes had any differentiation between control strategies. Overall, the effectiveness of the aggregator algorithm in reducing peak demand for all of the RBOs under its purview can be observed in Figure 11.

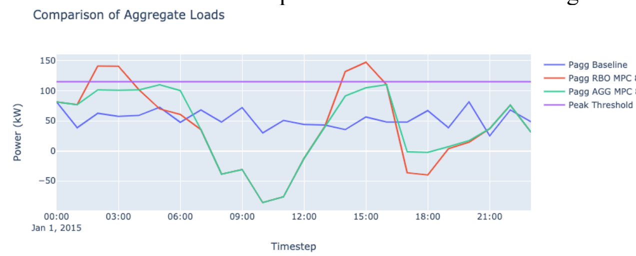

Figure 11 The AGG MPC Algorithm Effectively Limits Peak

6. Conclusions

In this paper, previous work [5,6] is used as a starting point for implementing an aggregator and distributed MPC framework for reducing peak demand across 20 residential buildings. Simplified RC models for the home and water heater system are used in all homes, while other homes contain an additional battery, PV system, or both. Individual homes optimize on a time-of-use based energy cost function with a reward price parameter, which is set by the aggregator to maintain aggregate demand below a specified threshold. The aggregator algorithm successfully reduces peak demand for a prediction horizon of 8 hours from 147 kW (without aggregator oversight) to 110 kW (with aggregator oversight).

6.1 Future Work

With respect to the convergence issue discussed (Figure 7 Figure 8), one of the things to notice is that battery charging and discharging only really happens in 5kW increments or until fully charged / discharged. It is unclear why homes don't implement minor step changes in battery charge / discharge behavior and is a topic for further investigation.

Another unfavorable condition in the current implementation is the requirement that heating and cooling can only occur in 1hr increments. This can be easily changed in the formulation of the water heater and home HVAC models, for example as follows:

$$T_{wh_i}^t = T_{wh_i}^{t-1} + \frac{\left[\frac{\left(T_{in_i}^t - T_{wh_i}^{t-1}\right)}{R_{wh_i}} + \frac{S_{wh_i}^t}{N}\cdot P_{wh_i}\right]\cdot \Delta t}{C_{wh_i}} \qquad (25)$$

$$S_{wh_i}^t \in \{0, N\} \qquad (26)$$

where N can act in a similar fashion to a duty cycle or minimum run time parameter. For example, N=4 would mimic a minimum 15-min runtime requirement for any of the home appliances. This should be a relatively straightforward modification, with the hope being that this allows more incremental changes in control strategy and better overall convergence.

Additional future work opportunities include:

- Providing consistent policies for implementing a demand response limit. The limit set in this paper was determined in an ad-hoc fashion (although based on limits seen by the initial RBO MPC run)
- Removing the strict temperature constraints and instead implement a thermal discomfort metric in the objective function so as to provide better convergence of optimal policy
- Investigate performance during other time periods (peak summer cooling)
- Utilize parallel processing, task management, or other technologies to monitor the size of the queue (number of

homes) and expand accordingly so as to improve algorithm run time

- Split the aggregator and RBO optimizer so as to run on separate devices so as to truly mimic the aggregator and distributed MPC paradigm

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