Assessing the Value of Uncertainty-Aware Transactive Control Framework for Commercial and Residential Buildings

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ABSTRACT

With the increasing adoption of renewable energy and electric vehicles in the power grid, dealing with uncertainty in both supply and demand is critical to ensuring reliable and efficient operations. In this study, we discuss the value of a two-stage stochastic control framework for an aggregator to address such problems by promoting improved decision-making and performance despite inherent uncertainty. An uncertainty-aware transactive control framework was developed to account for uncertainties in future conditions due to occupancy patterns, weather conditions, on-site power generation, and real-time pricing schemes. In the day-ahead period, the aggregator decides the electricity procurement plan considering the possible real-time control strategies for operation of the commercial building thermal energy storage (TES) assets and residential building electric water heaters. During real-time operations, the aggregator modulates controllable loads based on transactive market mechanisms with model predictive control (MPC). In order to evaluate the performance, this study quantified the expected value of perfect information (EVPI) and the value of the stochastic solution (VSS) to analyze the cost of uncertain information and potential benefits of solving the stochastic optimal control problem. This paper demonstrates how the stochastic solution of the developed framework can provide useful information for customers and grid operators in the management of uncertain situations to support grid reliability and sustainability.

1. INTRODUCTION

As new policies are introduced to address climate change, increased investments in renewable power sources are anticipated in support of bringing U.S. greenhouse gas emissions down to net-zero (Galvin and Healy, 2020). With a high penetration of renewable energy sources, the continued addition of clean energy production can become incrementally less useful unless it can be paired with energy storage or complimentary shifts in demand. Thus, potential solutions lie in technical and institutional changes on both demand and supply-side sources of flexibility (Cochran et al., 2015). As a form of flexibility, energy storage can compensate for the fluctuating output of renewable energy sources. An analysis by the National Renewable Energy Laboratory showed that adding controllable behind-the-meter energy storage can manage building peak demand and reduce electricity costs (Neubauer and Simpson, 2015).

In the meantime, the supply and demand of electricity must match in real-time. Not all systems have the flexibility to respond instantaneously, which means some level of centralized coordination is necessary. The grid operators need to know ahead of time to schedule the system operation for the following day. Thus, two-settlement market approaches with day-ahead and real-time settlement periods have been applied for managing electric grid operations. The day-ahead market allows for a credible plan to be developed based on anticipated future conditions, while the real-time market allows for the balancing of any differences between the day-ahead plan and actual conditions.

Although demand side flexibility can serve as an important resource for the grid, the availability and response magnitude can vary across time, building types, and system types, among other factors (Walnum et al., 2019). Correspondingly, it can be challenging to predict a building's potential flexibility given the uncertainty in occupant behavior, weather conditions, and on-site renewable energy generation. In our previous work, we developed an uncertainty-aware transactive control framework for commercial buildings with thermal energy storage (TES) assets participating in both the day-ahead and real-time market that can account for uncertainties in future conditions (Yu and Pavlak, 2020; Yu and Pavlak, 2021). In this study, we extend the framework to consider portfolios of residential buildings with controllable water heaters, and also incorporate behind-the-meter variable renewable generation as additional sources of uncertainty. In this work, the role of the aggregator is to decide the day-ahead electricity procurement plan and real-time operation strategy for residential and commercial building controllable thermal energy storage assets, accounting for uncertainty in occupant behavior, weather, variable generation, and grid prices. The performance of the framework is evaluated in terms of the value of the stochastic solution.

2. RELATED WORK

As a distributed control approach, transactive control has been introduced to manage electric grid operations (Liu et al., 2017). With increasing variability on both side of the meter, stochastic planning based on transactive control has been developed to contend with uncertainties in future conditions (Liu et al., 2018). A significant amount of past work has demonstrated the potential benefits of coordinating multiple energy resources with two-settlement market approaches over uncertain scenarios (Liu et al., 2018).

For the building sector, Hao et al. (2016) and Corbin et al. (2016) considered the application of transactive controls to commercial building Heating, Ventilation, and Air-Conditioning (HVAC) systems. Starke et al. (2019) and Adhikari et al. (2016) studied a transaction-based strategy to analyze the effectiveness in controlling residential building HVAC systems and water heater. Correa-Flrez et al. (2019) proposed an optimization model based on a transactive environment for a residential aggregator with PV, electric water heaters and batteries by controlling the settings of flexible devices. Robust optimization was used to consider uncertainty and a comparative study was performed. The results showed that using robust optimization allowed strategic bidding to capture uncertainties while complying with obligations in the wholesale and local markets. To integrate the flexibility potential of both residential and commercial buildings, Golmohamadi et al. (2019) proposed a central demand response provider to coordinate the plans of industrial and residential demand response aggregators. The aggregator used the thermal and electrical storage systems linked with on-site PV systems. The integrated flexibility was traded in the electricity market to maximize the profit of the market participants in a competitive environment. The results showed that the integrated flexibility could safeguard the future of power systems against intermittent power.

Based on the reviewed literature, there is an identified need to evaluate the value of the uncertainty-aware framework as well as the integrated flexibility potential of on-site PV generation in the portfolio. The value of the stochastic solution, which depends on the variation of the uncertain load scenarios, can be analyzed to maximize the potential benefits of the controllable demand side flexibility and support grid resiliency. This study evaluated the transactive control framework for an aggregator of both commercial and residential buildings with building emulator in real-time operation. The performance of the stochastic solution that accounts for uncertainties from the occupancy behavior, weather, PV generation, and market prices was analyzed to characterize the demand-side flexibility.

3. UNCERTAINTY-AWARE TRANSACTIVE CONTROL FRAMEWORK

3.1 Architecture of the control framework

In this paper, an uncertainty-aware transactive (UA-Tx) control platform with two separate market systems is proposed for an aggregator to dispatch energy to one group of commercial buildings and another group of residential buildings with thermal energy storage resources. Figure 1 highlights the architecture of the platform.

The control platform has two stages, one for day-ahead planning and one for real-time operation. In the day-ahead planning, the aggregator purchases electricity for the following day based on a two-stage stochastic optimization. The optimal procurement is determined to minimize the total cost by considering the expected operation of buildings with multiple uncertain scenarios. A set of scenarios is generated considering weather conditions, occupancy presence and absence patterns, domestic hot water use, appliance and electric equipment use, PV power generation, and real-time power prices as the sources of uncertainty. Scenarios were generated using a Monte-Carlo method. The detailed two-stage stochastic formulation is described in Section 3.2. In the real-time operation, the aggregator determines the operation of the TES charging/discharging for commercial buildings and water heater setpoint temperature changes for residential buildings based on the transactive market between the aggregator and buildings. The procured electricity, real-time power prices, and the actual building states are key factors for the aggregator to decide the operation and maximize its profit. Each building broadcasts its response curve representing constraints of the control and preferences as in Figure 1. As the aggregator clears the market price based on the information, the operation of building thermal energy storage resources is determined following the response curve of each building. A model predictive controller

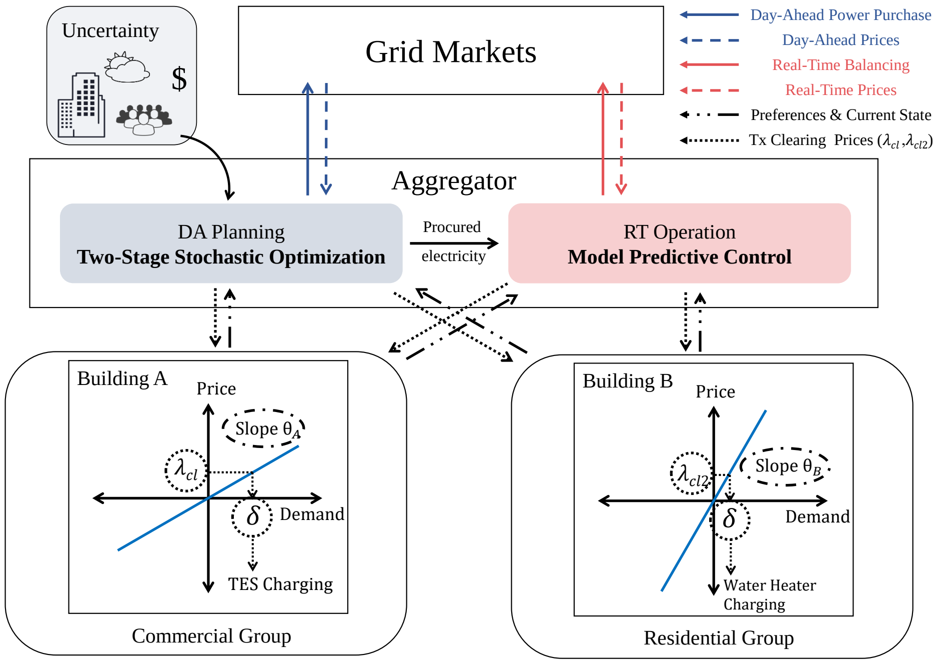

Figure 1: Architecture of the uncertainty-aware transactive building energy control platform.

(MPC) is used to modulate the amount of TES charging/discharging for the buildings in the commercial groups and the temperature setpoint of the water heaters for residential domestic hot water. In every time interval, the optimal control strategy is utilized in the energy management system (EMS) of the building emulator to simulate the response. In this work, detailed EnergyPlus models were used as the building emulators to verify the operation strategy from the control-oriented model. EnergyPlus EMS code was developed to implement the control strategies in the model. After executing the control strategy, the actual state is updated with the aggregator to solve the next time interval. The operation scheme of each commercial building with TES, described by the response curve, can be formulated as Eqs. (1)–(3) below,

$$\delta^c_{b,t} = \theta^c_b \lambda^{cl,c}_t \tag{1}$$

$$q^{c*}_{b,t} = q^c_{b,t} + \delta^c_{b,t} COP \tag{2}$$

$$p^{c*}_{b,t} = p^c_{b,t} + p^{oth,c}_{b,t} - p^{pv,c}_{b,t} + \delta^c_{b,t} = q^{c*}_{b,t}/COP + p^{oth,c}_{b,t} - p^{pv,c}_{b,t} \tag{3}$$

where, $\delta^c_{b,t}$ is the power compensation of the plant system by TES operation; θ^c_b is the coefficient for customer preference, representing the response curve's slope; $\lambda^{cl,c}_t$ is the cleared price between the aggregator and commercial building group; $p^{c*}_{b,t}$ is the actual power of commercial building in time interval t; $p^c_{b,t}$ is the commercial building electric demand before TES operation; and $p^{pv,c}_{b,t}$ is the power generation by the PV on the commercial building.

In every time interval, $\delta^c_{b,t}$ is determined by the response curve slope θ^c_b and the cleared price $\lambda^{cl,c}_t$ as in Equation (1). $q^{c*}_{b,t}$ is the modified heat transfer rate of plant system, which is defined as the sum of the original heat transfer rate $q^c_{b,t}$ and the power compensation multiplied by the coefficient of the system (COP) as in Equation (2). In TES charging mode, $q^{c*}_{b,t}$ is higher than the original rate since it considers the additional heat transfer rate of the chiller to storage. When it comes to TES discharging mode, $q^{c*}_{b,t}$ is lower than the original rate as the base chiller is operating at lower level. $p^{c*}_{b,t}$ is defined as the sum of the original electric demand $p^c_{b,t}$, other electrical loads from light and electric equipment $p^{oth}_{b,t}$ and the power compensation $\delta^c_{b,t}$ minus power supplied by PV generation on the site $p^{pv,c}_{b,t}$ as in Equation (3). In this work, the constant COP is used in the control-oriented model because of potential computational challenges of a more detailed model that accounts for dynamic changes in efficiencies. The value was set to reflect the efficiency of all components of the cooling plant (Henze et al., 2004). Although a constant COP is used in formulating a control-oriented model, the detailed building emulator captures the non-linear characteristics. The operation scheme of residential buildings with the water heater by the response curve can be formulated as Eqs. (4)–(6) below,

$$\delta^r_{b,t} = \theta^r_b \lambda^{cl,r}_t \tag{4}$$

$$q^{r*}_{b,t} = q^r_{b,t} + \delta^r_{b,t}/\mu \tag{5}$$

$$p^{r*}_{b,t} = p^r_{b,t}\mu + p^{oth,r}_{b,t} - p^{pv,r}_{b,t} + \delta^r_{b,t} = q^{r*}_{b,t}\mu + p^{oth,r}_{b,t} - p^{pv,r}_{b,t} \tag{6}$$

where, $\delta^r_{b,t}$ is the power compensation of the water heater; θ^r_b is the coefficient for customer preference; $\lambda^{cl,r}_t$ is the cleared price between the aggregator and residential building group; $p^{r*}_{b,t}$ is the actual power of residential building; and $p^r_{b,t}$ is the original residential building electric demand.

In every time interval, $\delta^r_{b,t}$ is determined by the response curve slope θ^r_b and the cleared price $\lambda^{cl,r}_t$ as in Equation (4). $q^{r*}_{b,t}$ is the modified heating demand of the water heater, which is defined as the sum of the original heating demand $q^r_{b,t}$ and the power compensation divided by the efficiency μ as in Equation (5). When the water heater is in charging mode, $q^{r*}_{b,t}$ is higher than the original rate since the heater is heated to set to the increased set temperature. In discharging mode, $q^{r*}_{b,t}$ is lower than the original rate as the water heater is not heated as much as it used to for the decreased set temperature. $p^{r*}_{b,t}$ is defined as the sum of the original electric demand $p^r_{b,t}$, other electrical loads from light and electric equipment $p^{oth}_{b,t}$ and the power compensation $\delta^r_{b,t}$ minus power supplied by PV generation $p^{pv,r}_{b,t}$ as in Equation (6).

3.2 Two-stage stochastic optimization framework

3.2.1 Scenario generation

To perform a two-stage stochastic optimization in day-ahead planning, a set of scenarios for the expected operation of the following day is needed. In this section, the generation of building load scenarios, weather scenarios, PV generation scenarios, and real-time power price scenarios is described.

The building load scenarios are generated with the detailed building energy simulation program EnergyPlus by changing the uncertain variables such as occupancy schedule, equipment usages, and weather conditions based on the building models. For the uncertain occupancy schedules of the commercial buildings, a Monte-Carlo approach is utilized to select a random occupancy schedule for the planning day from a year of occupancy schedule. The base full year of occupancy schedule data is created by using the stochastic occupancy model developed by Lawrence Berkeley National Laboratory (2017). When sampling a random schedule, holidays, and Sundays are filtered out. For the commercial buildings, the occupancy schedules are also used to schedule the lighting and other electric equipment usages in the building. The uncertain occupancy schedules of the residential buildings are generated based on Richardson's model, which is available for free download. The model is discussed in Richardson et al. (2008, 2010).

The occupant transition probabilities in the model are updated with the American occupant behaviors, which are extracted from the American Time Use Survey (ATUS) dataset from the Bureau of Labor Statistics. A Python script was developed to process the stochastic occupancy profiles into a format that can be updated in the building energy model of EnergyPlus. The domestic hot water (DHW) use and electricity use in the residential buildings are based on separate schedules of DHW usage scenarios and active occupancy by assuming their inactive (sleeping) time period from 11 PM to 5 AM. For the DHW event schedule, a Python script was developed to generate each DHW event schedule for dish washer, shower, sink, bath, and clothes washer, based on Hendron's probability distribution functions (PDF) (Hendron and Engebrecht, 2010). The number of DHW events during the planning day, start time, and duration are randomly selected based on the PDF and the occupants' active schedule. The generated schedule is written in a format of an hourly factor to utilize as schedules in EnergyPlus. For variation in the weather, the actual weather data from 2018 in Chicago, IL, is used. A 30-day period, centered on the planning day, is taken as the window from which to sample random weather scenarios. A weather file with the new random weather data for the planning day is read in EnergyPlus as input data. Based on the updated uncertain variables, one building load scenario is generated by running EnergyPlus. The weather variation is also used to create PV generation scenarios. The Model Chain function of the Python PV library was used to calculate the system output at a specific location (Holmgren et al., 2018).

For the real-time power prices, this work used a bootstrap approach based on the hourly distributions of deviations between day-ahead and real-time prices of the historical power prices to consider a reliable correlation between day-ahead and real-time power prices. The hourly price deviations are added to the day-ahead price of the planning day to create an uncertain real-time power price.

3.2.2 Two-stage stochastic formulation for day-ahead planning

In the two-stage stochastic optimal planning, the first-stage is related to the day-ahead procurement decision and the second-stage is representing building operating decisions based on the generated set of scenarios. In the optimal day-ahead planning, the procurement is decided to minimize the electricity procurement cost and expected real-time operation cost as in Equation (7),

$$\min_{x} \quad (\lambda^{DA})^T x + \mathbb{E}\left[\mathcal{Q}(x,\omega)\right] \tag{7}$$

where x is the vector of procured electricity in the day-ahead market; λ^{DA} is the vector of the power prices in the day-ahead market; $\mathbb{E}$ is the expected value of the real-time operation to calculate the probability-weighted sum over all the scenarios. The first term in Equation (7) is the day-ahead procurement cost and the second term is the expected cost in real-time operation. The second-stage objective can be expressed as Equation (8),

$$\begin{aligned}
\mathcal{Q}(x,\omega) = \min \quad & (\lambda_\omega^{cl,c})^T \sum_{b\in B_c} \delta_{b,\omega}^c + (\lambda_\omega^{cl,r})^T \sum_{b\in B_r} \delta_{b,\omega}^r + \lambda^{DR} 1^T (\sum_{b\in B_c} |\delta_{b,\omega}^c| + \sum_{b\in B_r} |\delta_{b,\omega}^r|) \\
& -\lambda^{ba} 1^T (\sum_{b\in B_c} p_{b,\omega}^{c,buy} + \sum_{b\in B_r} p_{b,\omega}^{r,buy} - \sum_{b\in B_c} p_{b,\omega}^{c,sell} - \sum_{b\in B_r} p_{b,\omega}^{r,sell}) + (\lambda_\omega^{rt'})^T (\sum_{b\in B_c} p_{b,\omega}^{c*} + \sum_{b\in B_r} p_{b,\omega}^{r*} - x) \\
& +\eta_1 [\quad \max(0, 1^T(x - 1.25(\sum_{b\in B_c} p_{b,\omega}^{c*} + \sum_{b\in B_r} p_{b,\omega}^{r*})))^2 + \max(0, 1^T(0.75(\sum_{b\in B_c} p_{b,\omega}^{c*} + \sum_{b\in B_r} p_{b,\omega}^{r*}) - x))^2 \quad]
\end{aligned} \tag{8}$$

where λ^{DR} is the demand response (DR) price in the transactive market; λ^{ba} is the base electricity price charged to the buildings; $\lambda_\omega^{rt'}$ is the uncertain real-time prices in scenario ω; $p_{b,\omega}^{c,buy}$ and $p_{b,\omega}^{r,buy}$ are the actual amount of power that the commercial and residential buildings buy from the aggregator; and $p_{b,\omega}^{c,sell}$ and $p_{b,\omega}^{r,sell}$ are the power that commercial and residential buildings sell to the aggregator. The first three terms in Equation (8) represent the cost that the aggregator pays to customers to reduce the building demand via the transactive market. Here, different clearing prices $\lambda_\omega^{cl,c}$, $\lambda_\omega^{cl,r}$ are provided to commercial and residential group, respectively, using the separate transactive markets. A fixed demand response price λ^{DR}, in addition to the clearing prices, provides additional compensation to customers for use of their TES resources. The fourth term is that the aggregator makes profits by selling the power to the buildings for their actual usage at a fixed price λ^{ba}, as well as the aggregator, purchases their extra electricity generated from the PV at the same price λ^{ba}. The fifth term is the balancing cost of aggregator in the real-time market. Depending on the procurement decision and actual power usage by customers, the aggregator may purchase more power or sell the extra power in the real-time market. In the day-ahead planning, the uncertain real-time price $\lambda_\omega^{rt'}$ is used. The sixth term is a penalty term to make sure the total day-ahead procured energy is within 25% of the sum of energy use in the expected real-time operation.

The first stage problem is subject to the procured electricity being positive and lower than the daily aggregated peak demand of the buildings as in Equation (9). p_b^h represents the peak demand of building in all scenario.

$$0 \le x \le \sum_{b\in B} p_b^h \tag{9}$$

The constraints of the second stage are described in Eqs. (10)–(15) for commercial buildings, and Eqs. (16)–(21) for residential buildings,

$$SOC_b^{min} \le SOC_{b,t,\omega} \le SOC_b^{max} \tag{10}$$

$$SOC_{b,t,\omega} = (q_{b,t,\omega}^{c*} - q_{b,t,\omega}^{c})/CAP_b^{tes} + SOC_{b,t-1,\omega} \tag{11}$$

$$p_{b,\omega}^{c*} = p_{b,\omega}^{c,buy} - p_{b,\omega}^{c,sell} \tag{12}$$

$$q_{b,\omega}^{c*}, p_{b,\omega}^{c,buy}, p_{b,\omega}^{c,sell} \ge 0 \tag{13}$$

$$q_{b,\omega}^{c*} - q_{b,\omega}^{c} \le \min(CAP_b^{ch}, (SOC_b^{max} - SOC_{b,t,\omega})CAP_b^{tes}) \tag{14}$$

$$\max(-q_{b,t,\omega}^{c}, (SOC_b^{min} - SOC_{b,t,\omega})CAP_b^{tes}) \le q_{b,t,\omega}^{c*} - q_{b,\omega}^{c} \tag{15}$$

$$T_b^L \le T_{b,t,\omega}^{dhw} \le T_b^H \quad (16)$$

$$T_{b,t,\omega}^{dhw} = \frac{(q_{b,t,\omega}^{r*} - q_{b,t,\omega}^{r})}{c_p \dot{m}} + T_{b,t-1,\omega}^{dhw} \quad (17)$$

$$q_{b,t,\omega}^{r*} - q_{b,t,\omega}^{r} \le \min(q_{max}^{dhw}, c_p \dot{m}(T_{b,t}^H - T_{b,t,\omega}^{dhw})) \quad (18)$$

$$c_p \dot{m}(T_b^L - T_{b,t,\omega}^{dhw}) \le q_{b,t,\omega}^{r*} - q_{b,t,\omega}^{r} \quad (19)$$

$$p_{b,t,\omega}^{r*} = p_{b,t,\omega}^{r,buy} - p_{b,t,\omega}^{r,sell} \quad (20)$$

$$q_{b,t,\omega}^{r*}, p_{b,t,\omega}^{r,buy}, p_{b,t,\omega}^{r,sell} \ge 0 \quad (21)$$

where $p_{b,\omega}^{h}$ is the hourly peak demand of building over all the scenario; $SOC_{b,t,\omega}$ is the state-of-charge (SOC) levels of TES in scenario ω; CAP_b^{tes} is the thermal energy storage capacity of the building b; CAP_b^{ch} is the capacity of the dedicated thermal energy storage chiller of the building b; $T_{b,t,\omega}^{dhw}$ is the set temperature of the water heater in scenario w; T_b^H is the maximum temperature of the water heater, T_b^L is the minimum temperature of the water heater, and q_{max}^{dhw} is the water heater capacity of the residential building.

The SOC levels of the TES are constrained within the specified lower and upper limit as in Equation (10). Also, the SOC level in each time interval is calculated with the TES heat transfer rate and the SOC level in the previous time interval as in Equation (11). The maximum TES charging rate cannot be over the minimum of the dedicated TES chiller capacity and the extra heat capacity of TES as in Equation (12). The maximum TES discharging rate is constrained by the maximum of the building cooling load and the rest thermal energy in TES as in Equation (13). The actual power of building $p_{b,\omega}^{c*}$ is defined as the power that the customers purchase from the aggregator and the power that they can sell to the aggregator. If the PV generates more than the building electric demand, the actual power $p_{b,\omega}^{c*}$ can be a negative value, which means they are selling their extra power to the aggregator as in Equation (14). Equation (16) constrains the temperature of the water heater within the specified range with a lower and upper limit. Equation (17) defines the water heater temperature in each time interval as calculated by the modified heating demand from the original demand. Equation (18) keeps the maximum charging energy limit by taking the minimum of the heater capacity and the extra heat capacity of the water heater considering the maximum temperature. Equation (19) restricts the maximum discharging rate by the rest of the thermal energy that the water heater can discharge considering the minimum temperature limit.

In the real-time operation, the aggregator modulates the operation of thermal energy storage resources of multiple buildings to minimize its total cost based on procurement in the day-ahead market and real-time power prices. The formulation of the MPC is nearly equivalent to the second stage of the two-stage stochastic optimization model with the exception that the penalty term is removed. The constraints for MPC model are the same as Eqs. (10)–(21).

4. CASE STUDY

4.1 Simulation conditions in case study

Simulation case studies were performed to evaluate the performance of the proposed control framework. The building models used in this study are three commercial and three residential buildings located in Chicago, IL. The commercial building model is the 5-zone example office model in EnergyPlus (U.S. Department of Energy, 2019), and a residential prototype building energy model with electric water heater and heat pump from the Department of Energy is used for the heating system. Then, the parameters of the building models were varied to generate three different commercial and residential building models. The main plant system configuration of the commercial building model consists of a base chiller (87.8 kW), TES dedicated chiller (23.4 kW), and TES (266 kWh). This work set the initial, minimum, and maximum SOC of TES as 100%, 0%, and 100% of TES capacity, respectively. The water heater tank of the residential building has a volume of 0.197 m^3 and the heater has a maximum capacity of 5.5 kW.

The case studies were performed for June 2018 and actual weather data from 2018 were used. The electricity prices in the day-ahead market were obtained from the historical data in 2018. In this work, the base electricity price λ^{ba} was set to be \$0.03/kWh. For the case studies presented in this work the demand response price λ^{DR} is was set to \$0.01/kWh. In this work, the performances of the framework for the aggregator with PV generation and the aggregator without considering PV generation were compared. The stochastic optimization and MPC controller model were developed in Python, and the solver MOSEK was used to solve the problem. This study utilized the expected value of perfect information (EVPI) and the Value of Stochastic Solution (VSS) analysis to evaluate the stochastic framework. EVPI is defined as the difference between the wait-and-see (WS) solution and the recourse problem (RP). WS represents the average profit that could be achieved if decisions could be made with knowledge of the uncertain variables, thus, EVPI can be thought of as a reasonable price to pay for a perfect forecast. VSS is defined as the difference between

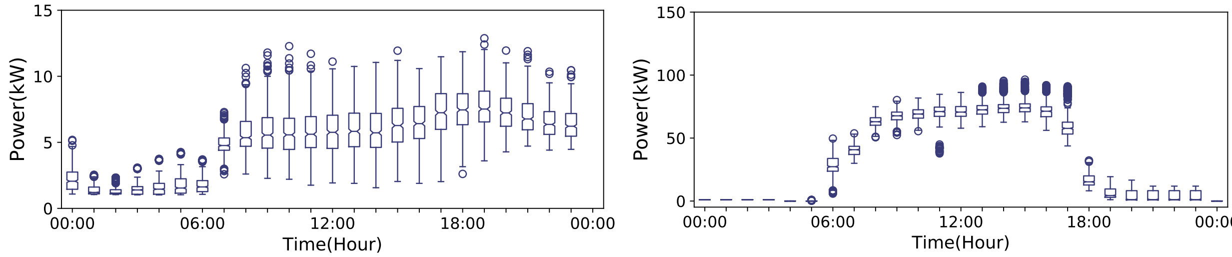

Figure 2: Stochastic load profile of residential (left) and commercial building (right) without PV (6/7).

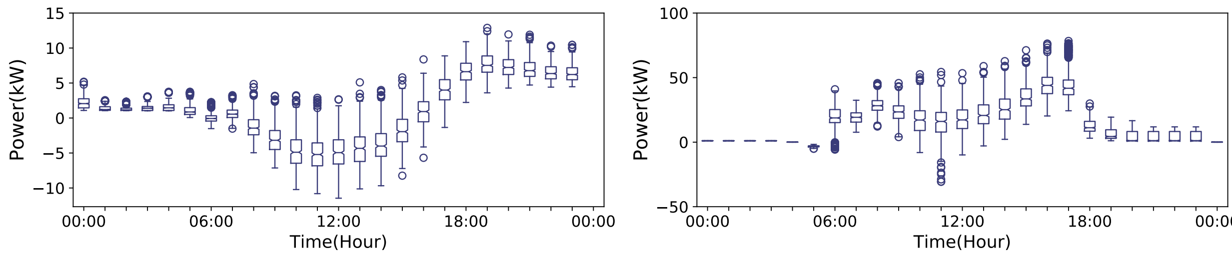

Figure 3: Stochastic load profile of residential (left) and commercial building (right) with PV (6/7).

the expected result of using the expected value (EEV) solution and RP. VSS represents the possible gain by solving the stochastic model, rather than simply adopting the mean value solution.

Figs. 2 and 3 provide samples of the stochastic load profile of 3 residential and 3 commercial buildings for one day. The left subfigure of Figure 2 represents the stochastic load profile of residential buildings without PV generation has a wide range of variation from 8:00 until midnight. It represents the uncertain occupant behavior for going to work and other activities. The stochastic load profile of commercial buildings without PV generation in the right subfigure has a relatively small variation in every hour during the operation. When the residential buildings install PV generation and widely use it for its electricity usage, the residential building has a variation in negative values during the daytime, since the PV output is greater than the required building load as in left subfigure of Figure 3. For the commercial building with PV generation in the right subfigure, it shows a relatively wider variation than the load profile without PV generation. Especially, when there is a peak PV generation at 11:00, it is expected that the commercial buildings can also sell the extra power to the aggregator.

4.2 Results

Table 1 highlights the overall results of case studies, in terms of WS, EEV, RP, EVPI, and VSS. For WS, EEV, and RP in Table 1, negative values indicate profit for the aggregator, and positive values indicate a loss. EVPI is quite large for each case, thus, the aggregator could benefit greatly from reducing uncertainty through gathering more information or improving forecasts. EVPI of the case with PVs can reach around 377% of RP as more uncertainties from the PV generation lead to much larger potential for profit and loss. Comparing both cases shows that the VSS/RP increased from 19% to 21% with increased variation.

Table 1: Summary of case study results with EVPI and VSS values.

	RP ($)	WS ($)	EEV ($)	EVPI ($)	EVPI/RP	VSS ($)	VSS/RP
No PV	-57.28	-199.2	-46.13	141.9	248 %	11.15	19 %
PV	-31.48	-137.7	-24.98	106.2	337 %	6.5	21 %

Figure 4 shows the detailed results of a single day (June 7th) for both cases. On that day, the real-time price spiked significantly from 15:00 to 18:00 as in Figure 6. The left and right subfigures represent the no PV and PV case, respec-

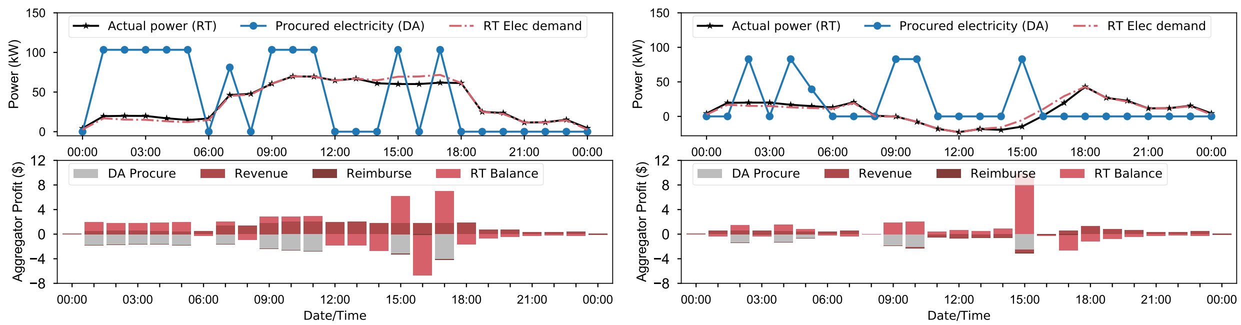

Figure 4: Detailed results of no PV case (left) and PV case (right) for June 7th.

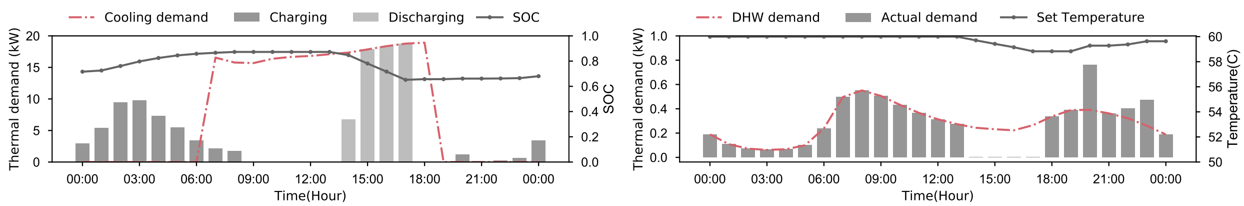

Figure 5: Stochastic load profile of residential (left) and commercial building (right) with PV (6/7).

tively. The top subfigures show the comparison of procured electricity, total electric demand (i.e., before operation of storage), and actual power (i.e., after operation of storage). Without consideration of PV generation on-site in the left subfigure, the aggregator purchased a large amount of power during morning hours and around 20% of electricity for the afternoon hours when the price spikes. When PV is included in the right subfigure, the majority of the power was procured during the early morning and afternoon. In this case, the actual power and the total electric demand are negative values from 10:00 to 15:00, which means the PV generated more power than the buildings needed. With the gap between them, it was confirmed that TES was utilized during the high priced hours. The second subfigure from the top shows the hourly objective function components of the aggregator for each hour of the day. The aggregator without PV made revenue by selling the power to customers during operating hours. Even though the aggregator had to purchase the power for the building demand at 16:00 when the price was high, the aggregator was able to make profits by selling the excess procured power in the real-time market. The interesting finding from the aggregator with PV is that the revenue values from 10:00 until 15:00 are negative as the aggregator purchased the power from the customers. It was able to make high profits by selling the power from the customers as well as the extra procured power in the real-time balancing market.

Figure 5 shows the TES operation of one commercial building in the left subfigure and the water heater operation of one residential building in the right subfigure. As expected, the TES is discharged when the real-time price is highest. The water heater also dropped the set temperature for discharging and increased it once the real-time price dropped below the day-ahead price.

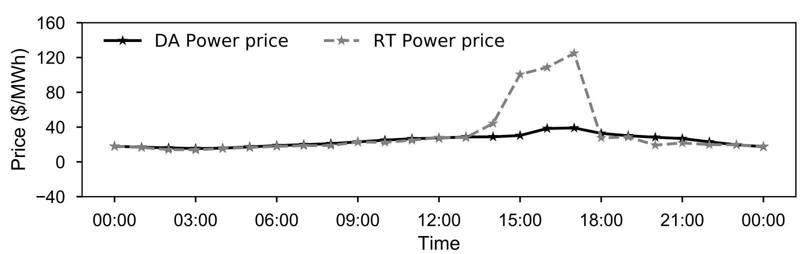

Figure 6: Day-ahead and real-time power price (6/7).

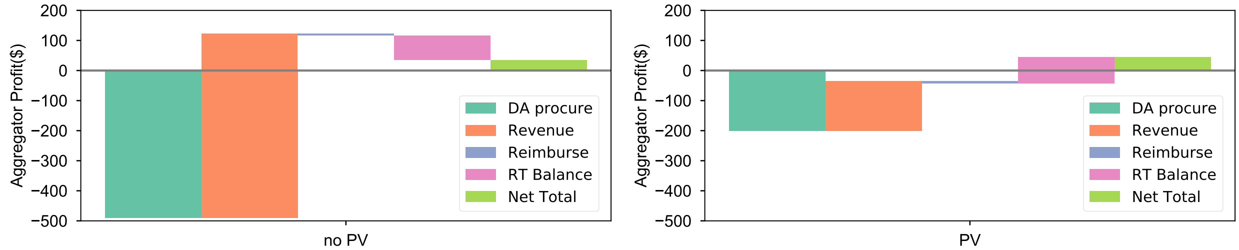

Figure 7: Stochastic load profile of residential (left) and commercial building (right) with PV (6/7).

Figure 7 shows the total surplus of the aggregator. Both cases made profits with different strategies. The aggregator without PV system in the left subfigure purchased a large amount in the day-ahead market and made large revenue by serving the power to the customers in real-time operation. However, it also needed to make purchases in the real-time balancing market to provide enough power to customers. For the case with PV in the right subfigure, the aggregator procured less power in the day-ahead market, made lower revenue from customers, and increased its profits from the real-time balancing market.

5. CONCLUSIONS

This work addresses the electricity procurement problem of the aggregator of both commercial and residential buildings with thermal energy storage assets. A two-stage stochastic programming approach has been proposed to account for uncertainties in future conditions with occupancy patterns, weather conditions, on-site power generation, and real-time pricing schemes in the decision process. To evaluate the capability of the proposed controller, the study conducted simulation experiments for portfolios with and without PV. It was observed that the proposed framework could offer the optimal procurement decisions for both cases and could offer the optimal TES operation scheme based on the customer's preference, and inherent uncertainty in the information available when making day-ahead decisions. From the EVPI and VSS analysis, it was observed that substantial benefits could be created by solving the stochastic program, especially when more uncertainties are included in the portfolio. The portfolio with PVs had higher EVPI/RP and VSS/RP than the portfolio without the PV generation on site. It was likely that the increased variability and uncertainty would potentially influence the results. This work highlights the increasing importance of accounting for uncertainty in operational decision making as load variability increase for future electric grids and microgrids with numerous distributed energy resources.

Future work can quantify the additional building-level benefits compared to individually optimized buildings. When PV is considered in the portfolio, the customers can sell their extra generated power to the aggregator at a constant rate regardless of the real-time power prices. The aggregator can shield customers from any price risk in the market. On the other hand, the individuals would deal with the risks of the fluctuating power prices in the market. Future work can also consider risk management to be beneficial for both the aggregator and customers against any financial risk.

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