Agent-based Privacy Preserving Transactive Control for Managing Peak Power Consumption

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***Abstract*—Many communities, such as college campuses, purchase electricity at a rate that includes a peak demand charge (averaged over 15-minute intervals). Managing energy cost and demand response requires actively managing the peak demand. In this paper, we develop transactive control mechanisms that enable buildings in an active distribution system or microgrid to cooperatively manage peak demand. A decentralized transactive control (DTC) approach is designed based on a novel decomposition algorithm that preserves the detailed load profile and information. By directly solving a mixed integer linear program, the scalable algorithm determines the optimal or near-optimal operating point for the system. Selected buildings on a real-world campus are used to evaluate the proposed platform. The results show the peak demand can be dramatically reduced while maintaining the largest possible building energy revenue.**

***Index Terms*—Privacy preservation, dual-projected subgradient, transactive control, energy management system, peak management.**

I. Introduction

WITH increased use of renewable energy resources and distributed energy management technologies, smart grid technologies offer the potential for significant efficiency improvements through market-based transactive exchanges between energy producers and consumers. Smart sensors and meters, communications and new methods for control and decision-making have the potential to transform our traditional, one-way electricity delivery into two-way bidirectional energy flow enabled by "transactive" mechanisms between utilities and behind-the-meter assets using new economic tools and processes. Such a "transactive energy" approach requires techniques for managing the generation, consumption and flow of electric power within an electric power system through the use of economic or market-based constructs while considering grid reliability constraints. Transactive energy techniques may be used to manage end-to-end (generation to consumption) electric power system activities using transactive control techniques [1] that facilitate the automatic, electronic transactions between energy providers and users about whether or not to sell or buy power [2]. To support the implementation of transactive energy and transactive control concepts, PNNL with support from the U.S. Department of Energy (DOE) has developed VOLTTRON [3], [4], [5], a distributed control and open-source sensing software platform for building energy management.

The increasing demand on building systems to achieve energy savings makes the development of smart building systems and related transactive control strategies more urgent and important than ever before. In particular, peak management is essential for any energy management strategy because the peak load in addition to the electricity consumption is used to determine the buildings energy bill. Also, the peak itself can impose threats to the stability of the grid as the system becomes more vulnerable when operating under high peak loading.

By managing peak demand, dispatchable building loads can be controlled to manage the energy budget for the campus. Various transactive control strategies and frameworks have been proposed for different aspects of electric power system operations [6], such as voltage management in distribution networks [7], [8], [9], frequency regulation [10], [11], and a variety of new electricity market mechanisms [12], [13], [14], [15]. There are a few works that are aimed at reducing peak load in building systems. Among them, a behind-the-meter transactive market is proposed in [16] for home energy management systems to achieve energy reduction by coordinating home appliances through market bidding and clearing. A transactive control market structure for commercial building HVAC systems with Agent bidding and market clearing strategies is presented in [17]. Though the occurrence of peak power consumption can

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be mitigated effectively via these methods, almost all of the above works neglect privacy concerns of the participants in the transactive control scheme.

Privacy preservation is another critical issue in developing the smart grid, and particularly, to the success of the deployment of transactive control strategies in smart buildings. The flow of user energy consumption data in smart grid systems may lead to the violation of user privacy. Inference on such data can expose the daily habits and the types of loads of inhabitants. There are significant ongoing efforts to protect privacy in smart grid. Common strategies include anonymizing and aggregating the metering data [18], [19], encryption of electricity usage [20], limited disclosure of data in decomposition framework [21], adding perturbing noises digitally or physically [22], [19]. Few works in the literature, however, have investigated privacy preserving in the context of transactive mechanism, especially when a model includes *integer variables*. It is interesting to consider privacy as a crucial part in the design of the transactive control approaches and frameworks.

The main contributions of this paper are summarized below.

1) A transactive control model is proposed to reduce the peak load and maximize the effective use of energy on the campus. By optimizing the combination of power profile bids generated by building participants, the model could effectively flatten the load curve and maintain the largest building energy revenue, while still meeting the operational requirements of the building. Generally, it is applicable in other smart buildings or microgrids.
2) We propose a novel decomposition algorithm and develop a decentralized platform, which preserves the detailed load profiles. By leveraging the Karush-Kuhn-Tucker (KKT) stationarity condition, the new subgradient-based algorithm converges efficiently. For the model in this study, we propose an analytical solution to subproblems. A method, no greater than linear time complexity, is developed to find the projected multiplier. The proposed approach is scalable and directly attain the optimal point or near-optimal point to a Mixed Integer Linear Programming (MILP) model. Privacy, such as electricity habits and behaviors, is effectively protected. The proposed algorithm can be applied to other optimization problems with similar structures.
3) We deploy and evaluate the transactive platform in selected buildings on a real-world campus grid, i.e., the Case Western Reserve University (CWRU) campus grid, by developing multiple Agents in VOLTTRON, an open source software, for campus level real-time transactive energy applications.

This paper is organized as follows. Section II introduces the transactive model and a centralized approach. The novel decentralized platform is proposed in Section III. Section IV presents the real-world campus deployment with VOLTTRON. Section V discusses results of case studies and Section VI concludes the paper.

II. Transactive Control Model

The decentralized transactive control (DTC) approach is different from centralized transactive control (CTC) approach, in the way that the Campus Agent is directly involved in control decisions. In the CTC approach, campus facilities (e.g. buildings and labs) will transact with the Campus Agent to enable optimization of the overall campus utility (the effective and efficient use of energy resources to accomplish building/lab operations), and the outcome is that each building has an agreed-upon schedule of average peak-power consumption over a given time interval. The DTC approach allow only buildings to participate in the transactions, without interference from the Campus Agent. Before introducing the strategies, several assumptions are made below.

1) Some building/lab loads are dispatchable and time-shiftable;
2) Buildings can calculate the utility of a load power profile given a number of time-varying inputs, such as inhabitants, availability of resources, internal deadlines, weather, and etc.;
3) Building Agents are able to negotiate with the users/activities in the facility as needed;
4) Distributed generation/storage are not explicitly considered but are expected to fit into the same mechanisms;
5) A supervisory mechanism will be added to monitor the performance of Building Agents and ensure they follow the rules of the transactive framework.

There are basically two phases in the CTC and DTC process: Phase 1 - bidding for peak power to support activities that require power over multiple periods, and Phase 2 - an auction to acquire any remaining available peak power at each period, which can be regarded as imbalance settlement.

A. Centralized Model

In general, several tasks are included in Phase 1:

1) Each building submits multiple bids for each activity that requires power over multiple periods. The bid includes a power-time profile and the utility that will be generated by performing that activity. For instance, Figure 1 illustrates three bids of consecutive power blocks (piecewise constant curves) required by the building to support an activity during the time period;

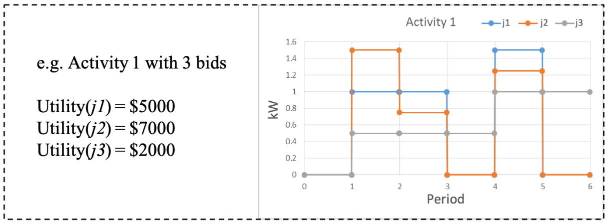

Fig. 1. Bidding example.

2) The overall Campus Agent reviews all bids and selects a combination that has the following properties: maximizes campus utility less peak energy cost; only one bid is awarded per building activity;

3) Winning bids are notified.

For an activity, Building Agent will produce bids, which include the power profile and utility value. The associated utility value, expressed in dollars, is a measure of the value the intended power consuming service/activity has for the campus. Agents construct as many bids as they desire for each activity. The motivation behind the activities concept is that an activity will stretch across multiple time periods and the power that is necessary for the activity in each period must be allocated for the activity to be accomplished successfully. Note that the planning periods do not necessarily need to be continuous, unless required by the specific activity.

The Campus Agent will receive a large number of bids from all Building Agent, and is responsible for selecting the combination of bids that maximizes the weighted campus utility. The net campus utility is comprised of the total utility for all selected activities minus the cost of maximal peak power over the planning period.

Denote b, i, j as the index of building, activity, and bid. Let $\mathcal{B}$, $\mathcal{I}_b, \mathcal{J}_i$, and $\mathcal{T}$ be the set of buildings, activities in building b, bids for activity i, and planning periods, respectively. $\mathcal{I} \triangleq \{\mathcal{I}_b\}_{b\in\mathcal{B}}$ denotes the set of all activities. For simplicity, an optimization problem without building index is modeled as

$$\max_{\boldsymbol{x},\phi} \quad \sum_{i\in\mathcal{I}}\sum_{j\in\mathcal{J}_i} x_{ij}u_{ij} - c\cdot\phi \tag{1}$$

$$(P) \quad \text{s.t.} \quad \sum_{i\in\mathcal{I}}\sum_{j\in\mathcal{J}_i} x_{ij}P_{ij,t} \le \phi, \quad t\in\mathcal{T} \tag{2}$$

$$\sum_{j\in\mathcal{J}_i} x_{ij} \le 1, \; i\in\mathcal{I} \tag{3}$$

$$x_{ij}\in\{0,1\}, \; i\in\mathcal{I}, j\in\mathcal{J}_i \tag{4}$$

where x_{ij} is binary variable and $\boldsymbol{x} \triangleq \{x_{ij}\}_{i\in\mathcal{I},j\in\mathcal{J}_i}$. $x_{ij}=1$ means that the j^{th} bid of activity i is selected in the planning period. If $i\in\mathcal{I}_b$, then activity i is within building b and Agent of building b produces $\mathcal{J}_i$ bids for activity i, where the bid consists of a power profile, $P_{ij,t}, t\in\mathcal{T}$, and a campus utility value, u_{ij}. From optimization perspective, the campus agent can drop building index as shown in problem (P). The objective function is total campus utility less dollar cost associate with peak load ϕ among planning periods. In general, the dollar cost is a function in ϕ. In this paper, we assume a proportional relationship $c\cdot\phi$. Constraint (3) means no more than one bid is selected for one activity.

It is observed problem (P) is an MILP problem. Following completion of the optimization, the Campus Agent will inform each of the Building Agents as to which bids are selected over that planning period.

B. Imbalance Settlement

Several tasks are involved in Phase 2, which is a period-by-period bidding process to address imbalance settlement after the transactive process in Phase 2:

1) Each building submits a bid (willing-to-pay price and kWh);
2) Market is cleared by Campus Agent based on cost per kW and power allocated in Phase 1;
3) Market clearing price is communicated back to Building Agents.

After all of the multi-interval activities have been scheduled, additional power at each interval is then made available to buildings for internal purpose or task not associated with short-term revenue generation. In order to allocate this power, the Campus Agent will host a traditional single, sealed bid auction for each interval. Once the auction from the first interval has closed, the second interval will be auctioned and so on, until all intervals have been closed.

The bids in this process consist of a desired power utilization curve and the associated price Building Agents are willing to pay at each breakpoint in the curve. Once the Campus Agent receives all bids, it aggregates bids into a single demand curve (price versus power), which is then compared against a supply curve generated by Campus Agent.

To generate the Campus Agent supply curve, the Agent calculates the marginal cost of each unit of energy over the interval. The marginal cost has two components 1) the cost of energy consumed and 2) a higher demand charge. Given these factors, the supply curve can be constructed. This curve can then be compared to the aggregated bid curve in order to compute the clearing price, the point of intersection of the two curves, as indicated in Figure 2. This is the point at which the buildings have agreed to purchase power from the campus at the same power-purchase-price required for the campus. This clearing price is communicated to each of the Building Agents, and then the next interval is auctioned off.

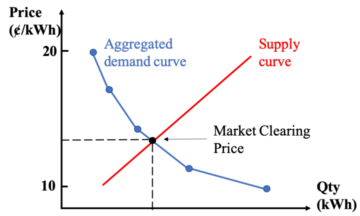

Fig. 2. Aggregated demand, supply and market clearing price illustration.

III. Privacy Preserving Decentralized Platform

A. Challenge Description

While it is attractive to maximize the utility of the power profile or lower the peak demand on campus, there are privacy concerns that need to be considered. With detailed load profiles for each building revealed, one could easily find out what activities are being conducted in the buildings. In order to obtain the awarded activities, the campus microgrid operator must have the load profile information for each building and each activity according to problem (P). One way to preserve privacy is to utilize decomposition methods.

By dropping the integer constraint (4), we relax Problem (P) into a new Linear Programming (LP) problem as given below.

$$\min_{\boldsymbol{x},\phi} \quad -\sum_i\sum_j x_{ij}u_{ij} + c\cdot\phi \tag{5}$$

$$\text{(P1)} \qquad \text{s.t.} \quad \sum_i\sum_j x_{ij}P_{ij,t} \le \phi,\ t\in\mathcal{T} \tag{6}$$

$$\sum_j x_{ij} \le 1, i\in\mathcal{I} \tag{7}$$

By dualizing constraint (6) with $\boldsymbol{\lambda} \triangleq \{\lambda_t\}_{t\in\mathcal{T}}$, we have Lagrangian function

$$\mathcal{L}(\boldsymbol{x},\phi,\boldsymbol{\lambda}) = -\sum_i\sum_j x_{ij}u_{ij} + c\cdot\phi + \sum_t \lambda_t\Big(\sum_i\sum_j x_{ij}P_{ij,t} - \phi\Big).$$

The standard Lagrangian relaxation method clearly does not apply in this problem, as the Lagrangian function above will be unbounded in the iteration process. In the literature, augmented Lagrangian relaxation is often introduced to overcome these kinds of issues. By adding quadratic terms, we then have

$$\mathcal{L}(\boldsymbol{x},\phi,\boldsymbol{\lambda}) + \frac{\rho}{2}\sum_t\left(\sum_i\sum_j x_{ij}P_{ij,t} - \phi\right)^2,$$

it then has a bounded solution and good convergence performance.

Unfortunately, the augmented Lagrangian has two main drawbacks: Firstly, the quadratic terms introduced above are not separable. There are effective methods to address this, such as Alternating Direction Methods of Multiplier (ADMM), recently well reviewed in [23]. However, this requires local copies of information from other buildings (privacy concern) and it also has a large communication overhead and computational burden. Secondly, the quadratic terms result in fractional elements in $\boldsymbol{x}$. We will show that the LP problem (P1) has an optimal integer vector $\boldsymbol{x}$ with mild conditions. However, the benefit of this is lost in the augmented Lagrangian relaxation approach even though it has the same objective value.

B. Dual-projected Subgradient Method

In this section, we will develop an information preserving platform based on a novel decomposition algorithm. The key idea is to find the subgradient direction based on the KKT stationarity condition. It addresses the challenge of the unbounded Lagrangian function. A beauty of the proposed method is that we could effectively get an *integer solution*. As stationarity condition results in constraints on dual variables, we call the proposed approach Dual-projected Subgradient (DPS) method. Furthermore, we discover the analytical solution to the subproblems and propose an efficient approach to directly calculate the projected subgradient direction.

Let $\{\lambda_t^*\}_{t\in\mathcal{T}}$ be the optimal multiplier. According to stationarity condition $\frac{\partial\mathcal{L}}{\partial\phi} = 0$, equality equation $\sum_t \lambda_t^* = c$ holds. Then equation

$$c\cdot\phi - \sum_t \lambda_t^*\phi = 0 \tag{8}$$

follows. Therefore, we could eliminate the term $c\cdot\phi - \sum_t\lambda_t\phi$ in the Lagrangian function by adding the constraint (8). A major benefit is that the objective becomes bounded. By introducing the optimality condition, we have a new Lagrangian function for each activity i

$$\mathcal{L}_i(\boldsymbol{x}_i,\boldsymbol{\lambda}) = \sum_j -x_{ij}u_{ij} + \sum_t\sum_j \lambda_t x_{ij}P_{ij,t},$$

where $\boldsymbol{x}_i \triangleq \{x_{ij}\}_{j\in\mathcal{J}_i}$. Problem (P1) can be recast as

$$\max_{\boldsymbol{\lambda}\in\Lambda} \quad \sum_i \min_{\boldsymbol{x}_i\in\mathcal{X}_i} \mathcal{L}_i(\boldsymbol{x}_i,\boldsymbol{\lambda}), \tag{9}$$

where

$$\Lambda \triangleq \Big\{\{\lambda\}_{t\in\mathcal{T}} | \sum_t \lambda_t = c, \lambda_t \ge 0\Big\},$$

and

$$\mathcal{X}_i = \Big\{\{x_{ij}\}_{j\in\mathcal{J}_i} | \sum_j x_{ij} \le 1, x_{ij}\in\{0,1\}\Big\}.$$

This means that the dual problem (9) is separated into I subproblems that could be solved independently by each Agent or building. Lagrangian multipliers are updated via

$$\boldsymbol{\lambda}^{k+1} = \Pi(\boldsymbol{\lambda^k} + \alpha^k \cdot \sum_i \sum_j x_{ij}^{k+1} \boldsymbol{P}_{ij}), \tag{10}$$

where α^k is the step size, and $\Pi(\cdot)$ denotes projection on the set Λ. We will show how to efficiently solve subproblems and attain the projection in Section III-D. The proposed algorithm is summarized below.

Algorithm 1 Dual-projected Subgradient Method (DPS)

1: Set $k = 0$, initialize $\boldsymbol{\lambda}^0, \boldsymbol{x}^0$, and tolerance δ
2: **while** $\|\boldsymbol{\lambda}^k - \boldsymbol{\lambda}^{k-1}\|_2^2 \geq \delta$ **do**
3:     **for** $i \leftarrow 1$ to I **do**
4:         $\boldsymbol{x}_i^{k+1} \in \arg\min_{\boldsymbol{x}_i \in \mathcal{X}_i} \mathcal{L}_i(\boldsymbol{x}_i, \boldsymbol{\lambda}^k)$
5:     **end for**
6:     Update $\boldsymbol{\lambda}^{k+1}$ according to (10)
7:     $k \leftarrow k + 1$
8: **end while**

One could choose different stopping criteria or step size. Broadly speaking, DPS method is a variant of the subgradient method based on the KKT stationarity condition. There is rich literature on the convergence of subgradient method [24]. Those convergence analyses apply to the DPS method as well.

C. Information Preserving

In the proposed platform, information broadcast can be in any aggregation level. The detailed activity load profiles, i.e. $P_{ij,t}$ and $u_{i,j}$, are concealed so that privacy is protected.

According to Algorithm 1, one only needs the value of total load in Step 6. Activities thus can be clustered into different groups for the aggregation purpose. For example, in a community with multiple buildings, Building b submits

$$D_{bt}^k \triangleq \sum_{i \in \mathcal{I}_b} x_{ij}^k P_{ij,t}$$

at iteration k, where $\mathcal{I}_b$ is the set of activities in building b. Only D_{bt}^k, the intermediate aggregated load for Building b, is disclosed or broadcast. When the algorithm converges, it reaches globally optimal even the detailed load profiles, i.e., $P_{ij,t}$ and u_{it}, are not disclosed.

Furthermore, two or more agents can reach an agreement to manipulate the aggregated data for more protection. For example, Building b and b' can respectively submit

$$D_{bt}^k - \xi_{bb'}^k \quad \text{and} \quad D_{b't}^k + \xi_{bb'}^k,$$

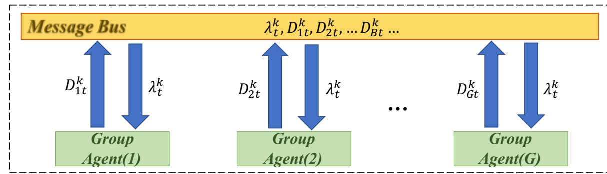

Fig. 3. Framework of decentralized platform. Building Agent submits value of aggregated load $D_{bt}^k = \sum_{i \in \mathcal{I}_b} x_{ij}^k P_{ij,t}$ anonymously. The multiplier is updated with aggregated campus-wide load by third party or Building Agent depending on settings.

where $\xi_{bb'}^k$ is a random perturbing noise. The algorithm DPS still converges as

$$(D_{bt}^k - \xi_{bb'}^k) + (D_{b't}^k + \xi_{bb'}^k) = D_{bt}^k + D_{b't}^k,$$

which does not affect the second term in equation (10). In other words, the algorithm works as long as perturbing noises are zero-sum. It is noted that D_{bt}^k is only used for calculating the campus-wide aggregated load, hence we do not need the identity information and it can be submitted anonymously.

To solve the optimization problem in Step 4 of Algorithm 1, each agent will need information of $\{\lambda_t^k\}_{t \in \mathcal{T}}$. Figure 3 illustrates a way of information broadcasting, where multiplier update only needs information of the last multiplier and the aggregated campus-wide load at iteration k.

D. Subproblem Minimization and Multiplier Update

$\mathcal{L}_i(\boldsymbol{x}_i, \boldsymbol{\lambda}^k)$ minimization problem has an analytical solution according to lemma below.

Lemma 1. Given multiplier $\boldsymbol{\lambda}^k$, we have objective value

$$\min_{\boldsymbol{x}_i \in \mathcal{X}_i} \mathcal{L}_i(\boldsymbol{x}_i, \boldsymbol{\lambda}^k) = \min_{j \in \mathcal{J}} \{-u_{ij} + \sum_t \lambda_t^k P_{ij,t}\}. \tag{11}$$

If $j^* \in \arg\min_{j \in \mathcal{J}} \{-u_{ij} + \sum_t \lambda_t^k P_{ij,t}\}$, then a minimum is

$$x_{ij}^{k+1} = \begin{cases} 1, & j = j^* \\ 0, & j \in \mathcal{J} \backslash j^*. \end{cases} \tag{12}$$

The proof is straightforward. To minimize $\mathcal{L}_i$, we only need to find an index j of minimal value in the $\{-u_{ij} + \sum_t \lambda_t^k P_{ij,t}\}_{j \in \mathcal{J}}$.

An important benefit is that we always have an integer minimum that is a feasible solution to original problem (P). A concern is the optimality gap and to address this we propose the lemma below.

Lemma 2. Let $\boldsymbol{\lambda}^*$ be the optimal multiplier for (P1). Let f^* and q^* be the objective value of (P) and (P1), respectively. If

$$j \in \arg\min_{j \in \mathcal{J}_i} \{-u_{ij} + \sum_t \lambda_t^* P_{ij,t}\} \tag{13}$$

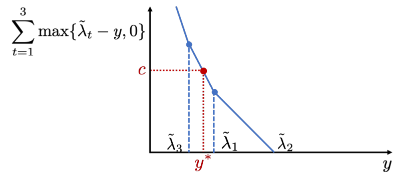

Fig. 4. Illustrative $\sum_t \max\{\tilde{\lambda}_t - y, 0\}$ with $\tilde{\lambda}_2 > \tilde{\lambda}_1 > \tilde{\lambda}_3$.

is unique for all $i \in \mathcal{I}$, then $f^* = q^*$.

It can be proved based on the uniqueness of Lagrangian function. In practice, the uniqueness for most i holds generally.

A remaining question in the proposed algorithm is how to efficiently find the projection of the subgradient on Λ. Fortunately, it is readily determined as shown below.

Lemma 3. Given set Λ and a direction $\{\tilde{\lambda}_t = \lambda_t^k + \alpha^k \cdot \sum_i \sum_j x_{ij}^{k+1} P_{ij,t}\}_{t \in \mathcal{T}}$, projection $\Pi(\tilde{\boldsymbol{\lambda}})$ on Λ is

$$\lambda_t^{k+1} = \begin{cases} \tilde{\lambda}_t - y^* & \text{if } y^* < \tilde{\lambda}_t \\ 0 & \text{if } y^* \geq \tilde{\lambda}_t, \end{cases} \tag{14}$$

and y^* is an unique solution to

$$\sum_t \max\{\tilde{\lambda}_t - y, 0\} = c.$$

Readers are referred to Appendix for the proof of Lemma 3. An illustrative example of attaining y^* is shown in Figure 4. It is observed that $\sum_t \max\{\tilde{\lambda}_t - y, 0\}$ is a piecewise function of y with breakpoints at $\tilde{\lambda}_t$. The projection is thus readily determined with simple calculation.

IV. Transactive Control with VOLTTRON

VOLTTRON provides an environment for Agent-based control and serves as a single point of contact for interfacing with devices (rooftop units, building systems, meters, etc.), external resources, and platform services such as data archiving and retrieving [25]. Among all the components, the Information Exchange Bus (IEB), or message bus is central to the system. All VOLTTRON Agents and services communicate through the message bus using the publish/subscribe (pub/sub) paradigm over a variety of topics. This provides a single interface that abstracts the details of devices and Agents from each other. Agents can use their own approaches and criteria in developing and executing various plans, and interacting with control devices by using the Actuator Agent to schedule and send commands. This allows VOLTTRON Agents to send control requests to various control devices connected to the message bus, e.g. using a Building Automation System (BAS) to manage building energy loads.

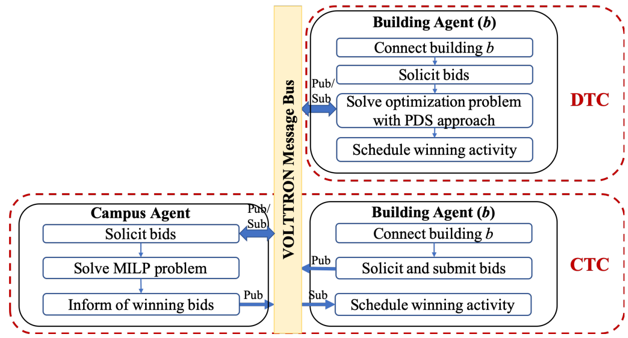

Fig. 5. DTC and CTC Agents framework in Phase 1

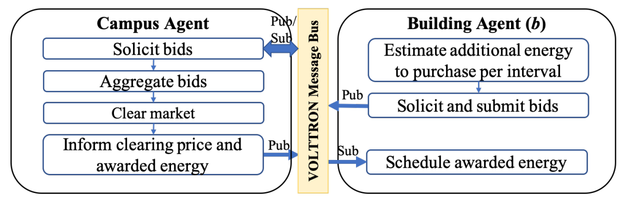

Fig. 6. Agents framework in Phase 2

Based on the above features, the Campus and Building Agents are developed for the DTC and CTC approaches in Phase 1 (Figure 5) and Phase 2 (Figure 6) respectively. With the customized Agent configuration file, the Building Agents may easily locate or link to specific building resources.

In each period, Building Agents generate their bids based on forecasted demand. In the DTC framework shown in Figure 5, the Building Agents are the only participants who solicit bids, optimizing and deciding which activities are selected. In Phase 2, the Campus Agent is the control center who is responsible for clearing the energy markets and informing participating Building Agents of the outcome.

V. Case Studies

We implement the proposed CTC and DTC strategies using facilities on the CWRU campus grid with a mix of measured and simulated energy data to illustrate their performance. CWRU buys its electricity from the Medical Center Company (MCCo), a district energy service provider. In this example, three campus buildings, i.e., MSASS, Olin and White, are participating in a 24-hour transactive control process. The electricity consumption of buildings are measured every 15-min by the building smart meters, and those of White building are simulated due to a lack of measurements. The Campus Agent is linked to MCCo and the Building Agents are linked to MSASS, Olin and White respectively. By packaging, installing and starting these Agents with customized configuration files, they are simultaneously running on the VOLTTRON platform.

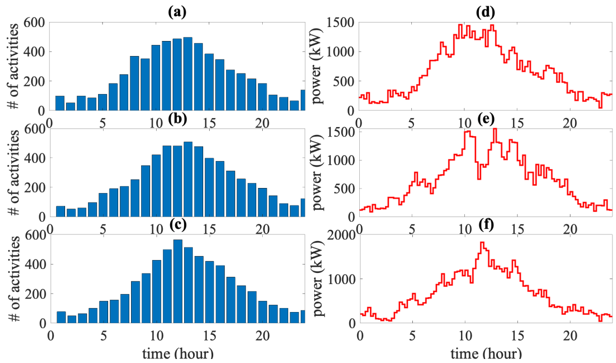

Fig. 7. Density of bidding activities by (a) MSASS (b) Olin and (c) White and awarded power for (d) MSASS (e) Olin and (f) White

Each Building has 500 different activities that span time periods from 15-min to one-hour all during the day. Three bids are generated for each activity including a forecasted power-time curve with a 15-minute time step, along with the utility value associated with this power profile. In this example, for simplicity, the utility is calculated as the energy consumed over the time period. The coefficient c is set to 0.1, and both the CTC and DTC approaches provide very close results. Hence, we present the results from the DTC approach when $c = 0.1$ unless specified otherwise.

Figure 7 demonstrates the density of 500 bidding activites generated by each building respectively, as well as the final awarded power curve after optimization in the 24-hour planning period. A larger density of the bidding activities around the middle of the day can be observed, which implies that at that period more activities want to take place resulting in higher peak demand. The awarded power curves are the accumulation of the winning activities. By summing up these curves for all three buildings we have the total optimal awarded power curve given in Figure 8, whose peak can be reduced by as much as 48.92%, compared to a typical solution without optimization. The total utility, however, increases 20.73% indicating increased benefits to the campus while the peak power has been efficiently managed.

With different coefficient c, various results are depicted in Figure 9. An interesting observation is that when c increases, the load curve changes to be more flattened at the peak. When higher weight is imposed to peak load term in the objective function, the proposed approach staggers load activities to avoid load spikes at any period as much as possible.

Figure 10 shows the convergence performance when $c = 10$. After around 25 iterations, the primal objective is attained based on the decentralized approach and

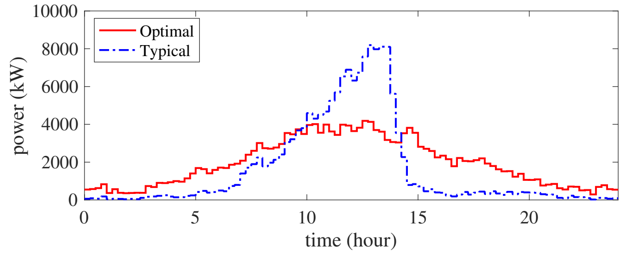

Fig. 8. The comparison of optimal and typical results for total power.

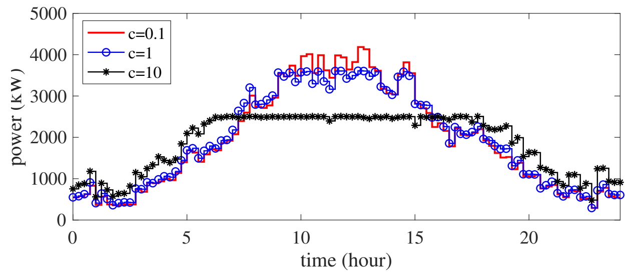

Fig. 9. Total power with different c. Increasing c flattens the curve.

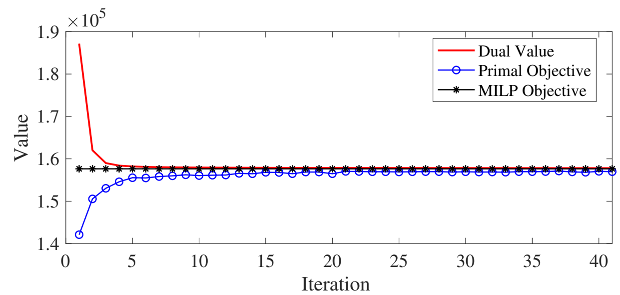

Fig. 10. Convergence performance. When $c = 10$, the optimality gap is 0.3%. When $c = 0.1$, the optimality gap is 0%.

the optimality gap is about 0.3%. The optimality gap decreases to 0 when c is changed to 0.1, validating Lemma 2. Compared to solving the MILP using Gurobi in the CTC approach, the proposed DPS method in the DTC approach is more efficient as shown in Column "$c = 10$" of Table I. While the MILP solver requires 100 seconds to get a solution with optimality gap 0.072% using Branch-and-cut method, the proposed algorithm attains a similar solution in less than one second. It is noted that the computational burden is linear with the number of activities or buildings, so the DTC approach is scalable and can be applied to large-scale systems. Table II demonstrates the percentage of the optimal solution difference between MILP and DPS methods. The binary optimal solutions $\boldsymbol{x}$ are same when $c = 0.1$ and slightly different when $c = 1$ and $c = 10$.

With the energy to support activities over the planning period, the buildings participate in auctions to acquire any remaining peak power in Phase 2 according to their

TABLE I
SOLUTION TIME COMPARISON

Approach	$c = 0.1$	$c = 1$	$c = 10$
Centralized (MILP)	0.049s	0.077s	100.028s
Decentralized (DPS)	0.021s	0.022s	0.022s

TABLE II
PERCENTAGE OF DIFFERENCE IN OPTIMAL SOLUTION $\boldsymbol{x}$

Scenarios	$c = 0.1$	$c = 1$	$c = 10$
Percentage of Difference in $\boldsymbol{x}$	0%	0.22%	1.64%

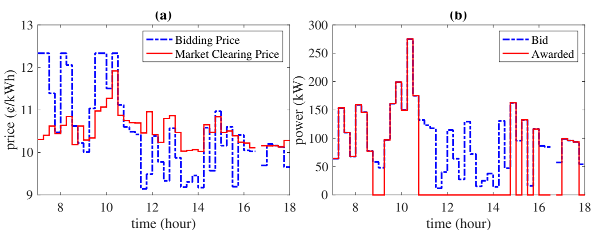

Fig. 11. Phase 2 (a) bidding price and market clearing price; (b) bid and awarded power for MSASS building.

real demand at 15-minute intervals throughout the day. Figure 11 shows the bidding prices versus market clearing prices, and the bidding power versus awarded power respectively for the MSASS building. Blank sections indicate periods when additional power is not needed. It is observed that at the peak of campus grid (between around Hours 10 and 15) less energy is awarded as a result of higher marginal cost; for other periods with lower total power demand, the opposite is true.

In order to test the scalability of the proposed approach, we add pseudo data and expand the system to 100 buildings. In the MILP approach, we set the MIPGap to 0.1%. Table III presents the solution time and optimality gap for MILP and DPS approaches. The DPS method generally converges around 20 iterations. As shown in column "Time", the computational advantage of DPS approach becomes even larger when the system size increases. For example, when there are 10 buildings, DPS approach converges in 0.046 seconds. In contrast, the solution time of MILP approach is 11.78 seconds being three orders of magnitude more time than DPS one. When the system has 100 buildings, DPS approach could find a solution within 0.4 seconds, but MILP approach requires more than 1456.4 seconds being four orders of magnitude more time than DPS one. On the other side, column "Opt. Gap" shows that solution quality of MILP approach is slightly better than that of DPS approach. The numerical testing shows that the optimality gap difference becomes smaller with the increase of building numbers. In practical applications, these difference is acceptable given the overwhelming computation and privacy advantage. It is noted that data

TABLE III
COMPARISON OF COMPUTATION PERFORMANCE WITH DIFFERENT SIZE SYSTEMS

# of Buildings	MILP		DPS	
	Opt. Gap	Time (s)	Opt. Gap	Time (s)
3	0.099%	2.24	0.3%	0.022
10	0.03%	11.78	0.18%	0.046
30	0.075%	110.2	0.094%	0.12
50	0.039%	334	0.081%	0.21
100	0.024%	1456.4	0.062%	0.4

in Table III is based on the step size of 1.0 for DPS approach. By tuning the step size, we could get even better solution quality for DPS approach. For example, in the system with 100 buildings, by changing the step size to 0.1, DPS approach finds the solution with optimality gap 0.02% in one seconds.

VI. CONCLUSION

This paper presents a transactive model together with a decentralized approach, to enable buildings in an active distribution system or campus to cooperatively manage the peak demand and maximize the utility of energy in supporting building operations. The decentralized approach allows buildings to handle the transactive process and decisions through bidding activities. The decentralized platform is based on a novel decomposition algorithm that preserves detailed load profile information. Selected buildings on a real-world campus grid are used to evaluate the proposed approaches with the Agents developed in the open-source VOLTTRON software platform. The results show that the peak power of the campus can be actively and effectively managed, and we observe that the decentralized approach often has significant performance in terms of solution time than the centralized approach and also has a clear advantage in preserving privacy. Future work will include the implementation of the proposed Agent-based platforms on other distribution systems or microgrids.

APPENDIX A
PROOF OF LEMMA 3

Proof. Finding the projection is equivalent to solve the optimization problem below

$$\min_{\boldsymbol{\lambda}\in\Lambda} \quad 1/2\|\boldsymbol{\lambda} - \tilde{\boldsymbol{\lambda}}\|^2.$$

According to KKT condition, we have

$$\sum_t \lambda_t^* = c,\ \lambda_t^* \geq 0,\ \beta_t^* \geq 0,\ \beta_t^*\lambda_t^* = 0,$$
$$(\lambda_t^* - \tilde{\lambda}_t) + y^* - \beta_t^* = 0$$

We eliminate β_t^*

$$\sum_t \lambda_t^* = c,\ \lambda_t^* \geq 0,\ (\lambda_t^* - \tilde{\lambda}_t + y^*)\lambda_t^* = 0,$$
$$(\lambda_t^* - \tilde{\lambda}_t) + y^* \geq 0.$$

If $y^* < \tilde{\lambda}_t$, then $\lambda_t^* > 0$ according to the third equation. We have $\lambda_t^* - \tilde{\lambda}_t + y^* = 0$ following complementary slackness condition. Hence, $\lambda_t^* = \tilde{\lambda}_t - y^*$ if $y^* < \lambda_t^*$. If $y^* \geq \lambda_t^*$, then we have $\lambda_t^* = 0$ according to the complementary slackness condition. Hence,

$$\lambda_t^* = \begin{cases} \tilde{\lambda}_t - y^* & \text{if } y^* < \tilde{\lambda}_t \\ 0 & \text{if } y^* \geq \tilde{\lambda}_t \end{cases}$$

As $\sum_t \lambda_t^* = c$, we have $\sum_t \max\{\tilde{\lambda}_t - y^*, 0\} = c$, which has an unique solution as $\sum_t \max\{\tilde{\lambda}_t - y, 0\} \in [0, +\infty)$ is a monotonously decreasing function of y. □

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