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Fully Decentralized Peer-to-Peer Energy Sharing Framework for Smart Buildings with Local Battery System and Aggregated Electric Vehicles

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Abstract

Decentralized peer-to-peer energy sharing techniques are highly promising to become the next-generation regime for smart building energy management, which can impulse the realization of nearly net-zero energy buildings. In this context, this paper proposes a comprehensive energy sharing framework for smart buildings in considering multiple dynamic components covering heating, ventilation, air conditioning (HVAC), battery energy storage systems (BESS) and electric vehicles (EVs). Specifically, both the power loss and shadow price of shared energy are explicitly modeled in a combined optimization framework, which is aimed to maximize the social welfare through peer-to-peer energy cooperation. Moreover, the role of agents acting as producers or consumers can be endogenously determined in the proposed model. In addition, distinguished with the classical distributed algorithms, we develop a fully decentralized algorithm based on dual-consensus version of alternating direction method of multipliers (DC-ADMM). The proposed algorithm avoids the need of coordinators at both the primal and dual variable updates in the iteration process, which suggests distinctive merits on high-level privacy protection as compared to most of the distributed optimization-based methods. Extensive case studies based on a smart building community demonstrate that the proposed peer-to-peer transactive framework can admirably improve the overall welfare for the involved smart buildings.

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1. Introduction

With the emerging technologies of Internet of Things (IoT) [1], conventional buildings are transformed into smart buildings, which features automated control and management of heating, ventilation, air conditioning (HVAC), lighting, battery energy storage system (BESS) and other ancillary systems [2]. More importantly, smart buildings enable greater improvement with respect to energy savings and efficiency, while assuring occupants comforts [3]. In fact, buildings are major energy consumers around the world, which account for over 40% of total energy use and carbon emissions, as reported by United Nations Environment Program[1] . The building sector in Hong Kong takes even more with over 93% of total electricity consumption[2] . Therefore, energy management in smart buildings is of vital importance in the process of urban low-carbon transition by effectually reducing carbon emissions.

Recently, the concept of peer-to-peer trading or sharing has emerged as a next-generation energy management regime among agents, such as commercial buildings and prosumers [4]. The pioneering works on peer-to-peer trading have been proposed on the mechanism in the microgrid [5], multiagent network [6], community battery control [7], smart homes [8]. Recent works show that, peer-to-peer energy sharing is promising to be achieved in the real-world implementation, with the advance of blockchain [9, 10]. However, the peer-to-peer energy sharing is confronted with unique challenges, including: 1) the energy sharing framework should be properly designed to preserve the information privacy of all participants. In other words, the less information exchanged, the better respect for building privacy; 2) it is complex to design an admirable payment scheme for the shared quantity of energy among participants. In general, the desirable pricing scheme should be fair to all participants. These two aspects are seemingly repulsive while promising to be investigated for future transactive energy development in smart buildings.

In recent years, there has been some existing work concerning the peer-to-peer energy sharing framework for smart buildings. As for the residential houses, Ref [11] builds a peer-to-peer energy trading platform to coordinate demand response with potential renewable energy generation. Ref [12] introduces

[1]International Energy Agency for the Global Alliance for Buildings and Construction. "Global Status Report 2017-Towards a zero-emission, efficient, and resilient buildings and construction sector," https://www.worldgbc.org/sites.

[2]Electrical and Mechanical Services Department. "Hong Kong Energy End-use Data 2019," https://www.emsd.gov.hk.

a new concept of energy classes via prosumer preferences to distinguish heterogeneous energy sources in peer-to-peer energy trading market. Refs [13] and [14] adopt auction-based approaches to clear the energy sharing market, in which the fraction of shared energy is determined by individual agents. The rooftop photovoltaic distributed generation is optimized by energy sharing framework in [15]. However, these works are necessarily in need of coordinators to a certain extent during the energy trading stage in the market, and thus the operation optimization is typically achieved in a centralized or partially centralized manner.

In considering the privacy concerns of agents, distributed optimization is more desirable in energy sharing market. Towards this end, game theoretic approaches are widely exploited to reformulated the problem [16]. For example, the peer-to-peer energy sharing problem is formulated as a non-cooperative Stackelberg game between prosumers in [17] and [18]. Moreover, it is shown in [19] that under the Stackelberg equilibrium, the total operational cost can be reduced and the utility can be maximized. In addition, Ref [20] demonstrates that the cooperative coalition game can also effectively reduce the energy cost via direct energy trading, while maintaining the local power balance. A decentralized algorithm is proposed in [21] to fully decouple the social welfare maximization problem.

To resolve the complex issue of pricing scheme in energy trading, Nash bargaining method is employed in [22], in which the profit incentives are ensured for all participants. Specially, in [23], a two-stage local transactive energy framework is formulated and the payment scheme is determined subsequent to the energy trading solution. Theoretically, one can prove the existence and Pareto optimality of the Nash equilibrium [22, 24]. Nevertheless, the mechanisms and general insights behind the resultant payment schemes are fairly unclear for participants. In [25], market power is firstly employed in energy trading to achieve a fair payment based on a modified bargaining method. In [26], a cost reduction ratio metric is devised to determine the payment according to the acceptable price range of all agents. The essential idea of these methods is to allocate the cost savings to agents in accordance with the proportion of their contribution over the entire scheduling horizon, e.g., one day.

In the literature, comprehensive modeling for energy sharing among smart buildings is rarely investigated. Firstly, a combined optimization model should be properly employed by accounting for the load dynamics, energy loss and optimal mutual payment. Secondly, it is a thorny task to foresee the role of prosumers acting as producers or consumers ahead of time. Thirdly, the decentralization level of the distributed algorithm exposes a large room of improvements by further reducing the local information exchanges among agents.

In consideration of the aforementioned challenges, this paper is aimed to propose a fully decentralized framework for energy sharing among smart buildings. The main contributions are threefold:

- A comprehensive energy sharing framework is proposed for the smart-building community, where individual buildings can flexibly manage the local HVAC loads, battery storage and electric vehicles. In the model, the role of agents to be a producer or a consumer is endogenously determined. Unlike most existing works, the proposed model need not calculate the energy surplus or deficiency before conducting the energy sharing plans.
- In addition, the transmission loss and shadow price are both integrated into the combined energy sharing model for the real-world implementation. Specifically, a pricing scheme is designed in the proposed framework, and the zero-sum term in the optimization model can be effectively handled in our model. Hence, a high-quality optimal and fair pricing solution can be obtained for all participant buildings.
- Furthermore, a fully decentralized algorithm is developed to solve the energy sharing problem based on a modified version of ADMM. The coordinator is completely removed in both the primal and dual variable updates. By deploying this, the information privacy of all buildings can be preserved to a great extent. Meanwhile, the global optimality and convergence can be ensured.

The remainder of the paper is organized as follows. In Section 2, we introduce the system model of smart buildings. Section 3 presents the problem formulation for energy sharing. A fully distributed algorithm without any coordinators is proposed in Section 4. Case studies and simulation results are reported in Section 5. Section 6 concludes this paper.

2. System Model of Smart Buildings

In this paper, we consider a community of smart buildings that are geographically close to each other, as shown in Fig. 1. These buildings are assumed to be connected to the main grid via the local distribution network, and also interacted with each other through bidirectional DC lines and communication networks. Mathematically, we denote $\mathcal{N} := \{1, 2, \ldots, N\}$ as the set of buildings, and $\mathcal{N}_i$ as the neighborhood set of building $i \in \mathcal{N}$.

Each of the smart buildings is assumed to contain local renewable generation, BESS, EVs, controllable load (e.g., HVAC units), and basic uncontrollable load. To facilitate the energy management and energy sharing, each building is deployed with a local Smart Building Energy Management System (SBEMS) that consists of necessary sensors and actuators. In this paper, we focus on the peer-to-peer energy sharing among smart buildings in a day-ahead market, which represents the mainstream marketplace for bulk electricity trading in practice. The horizon is entirely divided into $H = 24$ time slots and $\mathcal{T} := \{1, 2, \ldots, H\}$.

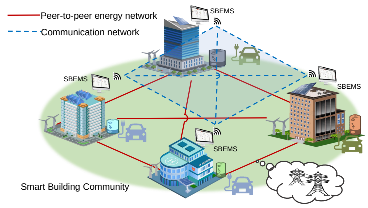


Figure 1: Peer-to-peer energy sharing framework of smart buildings.

2.1. Building Thermal Load

HVAC units are essential components in smart building energy management since they consume a large portion of energy in most circumstance (e.g., offices, hotels, and hospitals). HVAC units are expected to maintain an acceptable indoor comfort level for the occupants, of which the indoor temperature is normally a typical metric. According to the evolution law research of HVAC units [26], the indoor temperature of buildings is controlled following the equation:

$$T_{i,t}^{\text{in}} = \left(1 - \frac{1}{G_i R_i}\right) T_{i,t-1}^{\text{in}} + \frac{1}{G_i R_i} T_{i,t}^{\text{out}} - \frac{\eta_i}{G_i} P_{i,t}^{\text{h}}, \quad \forall t \tag{1}$$

where $T_{i,t}^{\text{in}}$ and $T_{i,t}^{\text{out}}$ are the indoor and outdoor temperature; $P_{i,t}^{\text{h}}$ represents the power consumption of HVAC units; G_i and R_i are internal parameters of HVAC units; η_i is the energy efficiency, of which $\eta_i > 0$ indicates the cooling mode while $\eta_i < 0$ indicates the heating mode, of building $i \in \mathcal{N}$.

In addition, the acceptable indoor temperature should be bounded within an operation range as expressed in (2), taking the technical limit into account.

$$T_{i,\min}^{\text{in}} \leq T_{i,t}^{\text{in}} \leq T_{i,\max}^{\text{in}}, \quad \forall t \tag{2}$$

Normally, during the occupancy periods, there is a set-point for the indoor room temperature at which the HVAC units attempts to maintain, e.g., $T_{\text{set}}^{\text{r}}$ in practice, which represents the desired comforts of the occupants. In this circumstance, the temperature setpoint $T_{\text{set}}^{\text{in}}$ is considered as the desirable temperature at which the HVAC units attempt to maintain. For instance, a comfortable indoor temperature is $22°C$, or within the range $[20°C, 24°C]$ in summer. Any temperature deviation from this setpoint incurs a namely discomfort of occupants.

2.2. Electric Vehicle Charging Model

EVs are emerging flexible loads in the smart buildings. EV patterns are taken into account in selecting proper charging strategies including immediate charging and smart charging at each time interval. it is assumed thatEV aggregators (EVA) are responsible for assembling the individual energy demands for the sake of overall management in smart buildings. EVA in the building can collect the specific EV information such as charging demand, arriving and departure time, maximal charging power and driver preferences, as long as it arrives at the building.

First of all, the dispatch ability of the newly arriving EV is evaluated by EVA at each time slot, according to the required time to fulfill the charging demand as per the maximal possible charging power:

$$t_{i,v}^{\mathrm{req}} = d_{i,v}^{\mathrm{EV}} / \min\left\{\bar{p}_{i,v}^{\mathrm{EV}}, \bar{p}^{\mathrm{charger}}\right\} \tag{3}$$

$$\begin{cases} \text{immediate charging,} & \text{if} \quad t_{i,v}^{\mathrm{req}} > t_{i,v}^{\mathrm{end}} - t_{i,v}^{\mathrm{st}} + 1; \\ \text{smart charging,} & \text{if} \quad t_{i,v}^{\mathrm{req}} \le t_{i,v}^{\mathrm{end}} - t_{i,v}^{\mathrm{st}} + 1 \end{cases} \tag{4}$$

where $d_{i,v}^{\mathrm{EV}}$ is charging demand of v-th EV in the building i , $\bar{p}_{v}^{\mathrm{EV}}$ represents the rated charging power of EV, $\bar{p}_{i}^{\mathrm{charger}}$ is rated power of the charger plot cable, $t_{i,v}^{\mathrm{req}}$ is the minimal required charging time, t_{v}^{st} and $t_{i,v}^{\mathrm{end}}$ are arrival and departure time, which means that the EV arrives at the beginning of time slot $t_{i,v}^{\mathrm{st}}$, while leaves at the end of time slot $t_{i,v}^{\mathrm{end}}$. In (3), the maximal charging power is utilized to calculate $t_{i,v}^{\mathrm{req}}$, and then it is compared to the parking duration when determining whether the EV charging demand is dispatchable, as in (4). For clarity, we define the rated charging power as $p_{i,v}^{\mathrm{rated}}$, to capture the maximal charging power of EVs:

$$p_{i,v}^{\mathrm{rated}} = \min\left\{\bar{p}_{i,v}^{\mathrm{EV}}, \bar{p}_{i}^{\mathrm{charger}}\right\} \tag{5}$$

EVs with immediate charging are treated as inflexible load to the system, as the charging power takes the maximal possible value. On the other hand, EVs with smart charging strategies are regarded as flexible load as the charging power is dispatchable. In consideration of this, EVs refer to the dispatchable EVs in the rest of the paper, for simplicity. The charging demand, under the smart charging strategy, should be fulfilled during the parking time interval as follows:

$$d_{i,v}^{\mathrm{EV}} = \sum\nolimits_{t=t_{i,v}^{\mathrm{st}}}^{t_{i,v}^{\mathrm{end}}} \eta p_{i,v,t}^{\mathrm{EV}} \Delta t \tag{6}$$

$$0 \le p_{i,v,t}^{\mathrm{EV}} \le p_{i,v}^{\mathrm{rated}}, t \in \left[t_{i,v}^{\mathrm{st}}, t_{i,v}^{\mathrm{end}}\right] \tag{7}$$

where η is the charging efficiency; $p_{i,v,t}^{\mathrm{EV}}$ is the charging power of EV v of building i at time interval t, which is non-negative in the charging available periods $[t_{v}^{\mathrm{st}}, t_{v}^{\mathrm{end}}]$, and smaller than the rated power p_{v}^{rated}. The integration of large number of EVs would result in a rapid increase of variables, and thus lead to difficulty in the problem formulation and solution seeking. According to [27], this paper regards the EVA charging power as a whole in the problem, which is formulated as follows:

$$P_{i,t}^{\mathrm{EVA}} = \sum\nolimits_{v=1}^{V_i} p_{i,v,t}^{\mathrm{EV}} \tag{8}$$

where $P_{i,t}^{\mathrm{EVA}}$ is the total charging power of building i. In this regard, the EVA charging power is regarded as the variable to satisfy the charging energy demand as follows:

$$E_{i,t}^{\mathrm{EVA}} = \sum\nolimits_{\tau=1}^{t} \eta P_{i,\tau}^{\mathrm{EVA}} \Delta t \tag{9}$$

$$E_{\min,i,t}^{\mathrm{EVA}} \le E_{i,t}^{\mathrm{EVA}} \le E_{\max,i,t}^{\mathrm{EVA}} \tag{10}$$

$$0 \le E_{i,t}^{\mathrm{EVA}} - E_{i,t-1}^{\mathrm{EVA}} \le P_{i,\max}^{\mathrm{EVA}} \tag{11}$$

where $P_{i,t}^{\mathrm{EVA}}$ is the aggregated charging power of EVs, $E_{i,t}^{\mathrm{EVA}}$ denotes the accumulated recharged energy of EVA, and (10) implies that the recharged energy trajectory is upper-bounded by $E_{\max,i,t}$, and lower-bounded by $E_{\min,i,t}$, which are derived by Maximal-Power-Forward-Backward Method, as in the following equations:

$$E_{\max,i,t}^{\mathrm{EVA}} = \sum\nolimits_{v=1}^{V_i} \left[\sum\nolimits_{\tau=t_{i,v}^{\mathrm{st}}}^{t} \eta p_{i,v}^{\mathrm{rated}} \Delta t \right]_0^{d_{i,v}^{\mathrm{EV}}} \tag{12}$$

$$E_{\min,i,t}^{\mathrm{EVA}} = \sum\nolimits_{v=1}^{V_i} \left[d_{i,v}^{\mathrm{EV}} - \sum\nolimits_{\tau=t}^{t_{i,v}^{\mathrm{end}}} \eta p_{i,v}^{\mathrm{rated}} \Delta t \right]_0^{d_{i,v}^{\mathrm{EV}}} \tag{13}$$

where the notation $[\cdot]_a^b$ means that the value is projected onto the interval $[a, b]$.

2.3. Battery Energy Storage System

Distinguished from the traditional buildings, smart buildings can involve newly emerged BESS in energy management through SBEMS. Via charging and discharging actions, BESS can help smart buildings smoothen out the intermittence of the renewable energies. However, frequent discharging behaviors would inevitably cause degradation of battery life cycles [28]. Therefore, it is essential to model the degradation cost of BESS by considering necessary operational constraints.

Given that the building $i \in \mathcal{N}$ has installed a BESS, the following constraints capture the operation features of the BESS at each time slot.

$$S_{i,t} = (1 - \eta_i^{\mathrm{bat}}) S_{i,t-1} + \eta_i^{\mathrm{ch}} P_{i,t}^{\mathrm{ch}} \Delta t - P_{i,t}^{\mathrm{dis}} / \eta_i^{\mathrm{dis}} \Delta t \tag{14}$$

$$S_{i,\min} \le S_{i,t} \le S_{i,\max} \tag{15}$$

$$S_{i,H} \ge S_{i,0} \tag{16}$$

$$0 \le P_{i,t}^{\mathrm{ch}} \le \bar{P}_i^{\mathrm{ch}} s_{i,t}^{\mathrm{ch}} \tag{17}$$

$$0 \le P_{i,t}^{\mathrm{dis}} \le \bar{P}_i^{\mathrm{dis}} (1 - s_{i,t}^{\mathrm{ch}}) \tag{18}$$

$$s_{i,t}^{\mathrm{ch}} - s_{i,t-1}^{\mathrm{ch}} \le u_{i,t}^{\mathrm{bat}}, s_{i,t-1}^{\mathrm{ch}} - s_{i,t}^{\mathrm{ch}} \le u_{i,t}^{\mathrm{bat}} \tag{19}$$

$$\sum_{t\in\mathcal{T}} u_{i,t}^{\mathrm{bat}} \leq U_i^{\mathrm{bat}} \tag{20}$$

where $S_{i,t}, P_{i,t}^{\mathrm{ch}}$ and $P_{i,t}^{\mathrm{dis}}$ denote the stored energy, charging and discharging power of the BESS i at time slot t, $\eta_i^{\mathrm{bat}}, \eta_i^{\mathrm{ch}}, \eta_i^{\mathrm{dis}} \in (0,1)$ are self-discharging, charging and discharging efficiency, binary variable $s_{i,t}$ denotes the charging or discharging states and binary variable $u_{i,t}^{\mathrm{bat}}$ records the state switching numbers, respectively. The time-coupling constraint (14) represents the evolutionary process of energy storage levels in the BESS, (15) indicates that the energy level is bounded into a permissible range; one should also restrict the terminal energy level for no less than the initial level $S_{i,0}$ as indicated in (16); moreover, the charging and discharging power are capped by their maximal values in (17) and (18), (19)and (20) limit the total charging/discharging state switching numbers over the scheduling horizon, for the safety of batteries.

2.4. Total Cost of Building Without Energy Sharing

To supply the local demands in smart buildings, renewable energies, BESS and the utility are three main sources that can be fully involved. As such, the active power balance in each building is concluded as follows:

$$P_{i,t}^{\mathrm{buy}} + P_{i,t}^{\mathrm{dis}} + P_{i,t}^{\mathrm{re}} = P_{i,t}^{\mathrm{L}} + P_{i,t}^{\mathrm{h}} + P_{i,t}^{\mathrm{EVA}} + P_{i,t}^{\mathrm{ch}} + P_{i,t}^{\mathrm{sell}} \tag{21}$$

where the left-hand side of (21) corresponds to the energy supply, while the right-hand side corresponds to the energy consumption in the building, in which $P_{i,t}^{\mathrm{re}}$ denotes the available renewable energies, and $P_{i,t}^{\mathrm{L}}$ denotes the uncontrollable load, $P_{i,t}^{\mathrm{buy}} \geq 0$ denote the quantity of energy purchased from the utility company and $P_{i,t}^{\mathrm{sell}} \geq 0$ denotes the surplus energy sold to the utility, by the building $i \in \mathcal{N}$ at t-th time slot. Due to the physical limit F_i, the energy exchange with the utility should be subject to:

$$-\bar{F}_i \leq P_{i,t}^{\mathrm{buy}} - P_{i,t}^{\mathrm{sell}} \leq \bar{F}_i \tag{22}$$

If the building i does not participate in the peer-to-peer energy sharing with other buildings, the SBEMS of the building will try to minimize the utility trading, as well as the occupant discomforts:

$$\begin{aligned} \widetilde{C}_{i,t} =& \beta_i \left(T_{i,t}^{\mathrm{in}} - T_{\mathrm{set}}^{\mathrm{in}}\right)^2 \Delta t + \kappa_i^{\mathrm{bat}}(P_{i,t}^{\mathrm{ch}} + P_{i,t}^{\mathrm{dis}})\Delta t \\ &+ \left(\mu_t^{\mathrm{b}} P_{i,t}^{\mathrm{buy}} - \mu_t^{\mathrm{s}} P_{i,t}^{\mathrm{sell}}\right) \Delta t, \quad \forall t \end{aligned} \tag{23}$$

where β_i is introduced to denote the discomfort cost coefficient of building $i \in \mathcal{N}$, κ_i^{bat} is the amortized cost of charging and discharging of batteries, μ_t^{b} and μ_t^{s} are utility buying and selling price.

Given this context, the corresponding SBEMS is aimed to seek an optimal energy schedule scheme by solving the following optimization problem individually:

P0: Building's Optimization Without Energy Sharing

$$\begin{aligned} \text{minimize} \quad & \sum\nolimits_{t\in\mathcal{T}} \widetilde{C}_{i,t} \\ \text{subject to} \quad & \text{(1)-(22)} \end{aligned}$$

It is noticed that **P0** is convex, and thus can be readily solved. Further, let $\bar{C}_i$ denote the optimal value of **P0**, which suggests the operation cost of building $i \in \mathcal{N}$ without energy sharing.

3. Problem Formulation with Energy Sharing

In this section, the proposed framework of peer-to-peer energy sharing and the optimization problem formulation will be presented.

3.1. Energy Sharing Model

Peer-to-peer energy sharing is a promising alternative to direct trading with the utility company, where buildings can self-organize to resolve the energy surplus or deficit problem via exchanging energy with each other in a fully distributed manner. By doing so, the interconnected buildings can enable the diversities of energy supply and demand patterns while achieving reduced energy costs. Specifically, each building is allowed to buy/sell energy from/to any other buildings under the private transaction contract (including energy sharing quantities and prices).

Consider a bilateral energy sharing between building $i \in \mathcal{N}$ and building $j \in \mathcal{N}_i$, and it is assumed that there is a $\epsilon \in (0,1)$ power loss on the link (i,j)[29]. Then, the power exchange balance on the link is formulated as follows:

$$e^{i\to}_{ij,t}(1-\epsilon) = e^{\to j}_{ji,t}, \quad e^{\to i}_{ij,t} = e^{j\to}_{ji,t}(1-\epsilon) \tag{24}$$

$$0 \le e^{i\to}_{ij,t} \le F^{\mathrm{p}}_i y^{i\to}_{ij,t}, \quad 0 \le e^{\to i}_{ij,t} \le F^{\mathrm{p}}_i y^{\to i}_{ij,t} \tag{25}$$

$$y^{\to i}_{ij,t}, y^{i\to}_{ij,t} \in \{0,1\}, \quad y^{\to i}_{ij,t} + y^{i\to}_{ij,t} \le 1 \tag{26}$$

where the first equation of (24) describes the case of power flowing from i to j, in which $e^{i\to}_{ij,t}$ represents the exported power from i, and $e^{\to j}_{ji,t}$ is the power received by j; while the second equation of (24) describes the case of power flowing from j to i, in which $e^{j\to}_{ji,t}$ is the power exported by j, while $e^{\to i}_{ij,t}$ is the power received by i. (25) and (26) introduce the binary variables to label the energy exchange directions and the exchange power line capacity, which means that at most one power flow direction can exist in the power link (i,j).

Observing the energy sharing equation model, one should notice that the variables $e^{i\to}_{ij,t}$ and $e^{\to i}_{ij,t}$ represent the energy from/to the end of building i, while the variables $e^{j\to}_{ji}$ and $e^{\to j}_{ji,t}$ are energies from/to the end of building j. Towards this end, we introduce two variables $e^{j}_{i,t}$ and $e^{i}_{j,t}$ to collect above two equations for simplicity, which are defined by:

$$e^{j}_{i,t} = e^{\rightarrow i}_{ij,t} - e^{i\rightarrow}_{ij,t}(1-\epsilon) \tag{27}$$

$$e^{i}_{j,t} = e^{\rightarrow j}_{ji,t} - e^{j\rightarrow}_{ji,t}(1-\epsilon) \tag{28}$$

By doing so, the power exchange balance equation (24) is reformulated as follows:

$$e^{j}_{i,t} + e^{i}_{j,t} = 0, \quad \forall i \in \mathcal{N}, \forall j \in \mathcal{N}_i, \forall t \tag{29}$$

In addition, the power balance constraints are formulated as follows:

$$\begin{aligned} P^{\text{buy}}_{i,t} + P^{\text{dis}}_{i,t} + P^{\text{re}}_{i,t} + \sum_{j\in\mathcal{N}_i} e^{\rightarrow i}_{ij} &= P^{\text{L}}_{i,t} + P^{\text{h}}_{i,t} \\ &+ P^{\text{EVA}}_{i,t} + \sum_{j\in\mathcal{N}_i} e^{i\rightarrow}_{ij} + P^{\text{ch}}_{i,t} + P^{\text{sell}}_{i,t} \end{aligned} \tag{30}$$

3.2. Clearing the Shared Energy

The energy sharing price is another critical part in the peer-to-peer transaction. Let $\lambda^{j}_{i,t}$ denote the energy price of building i set for building j, at t-th time slot. For any successful mutual energy sharing pairs, the following price agreement should be satisfied:

$$\lambda^{j}_{i,t} = \lambda^{i}_{j,t}, \quad \forall i \in \mathcal{N}, \forall j \in \mathcal{N}_i, \forall t \tag{31}$$

Though buildings participate in energy sharing, they are still considered as independent and self-motivated agents. Thus, the new cost function for each participant building $i \in \mathcal{N}$ will become:

$$\sum_{t\in\mathcal{T}} \left(\widetilde{C}_{i,t} + \boldsymbol{\lambda}^{\text{T}}_{i,t}\mathbf{e}_{i,t} \right) \tag{32}$$

where vectors $\boldsymbol{\lambda}_{i,t} := \{\lambda^{j}_{i,t}\}_{j\in\mathcal{N}_i}$ and $\mathbf{e}_{i,t} := \{e^{j}_{i,t}\}_{j\in\mathcal{N}_i}$ collect the energy sharing price and amount profiles of building i with all neighbors at t-th time slot; the notation $(\cdot)^{\text{T}}$ denotes the transpose operation. In (32), the first term is the internal cost defined in (23) and the second term denotes the payment to other buildings.

Therefore, for the smart building community with energy sharing, the social welfare maximization problem can be expressed as follows:

SW-Social Welfare Maximization

$$\begin{aligned} \text{maximize} \quad & -\sum_{i\in\mathcal{N}}\sum_{t\in\mathcal{T}} \left(\widetilde{C}_{i,t} + \boldsymbol{\lambda}^{\text{T}}_{i,t}\mathbf{e}_{i,t} \right) \\ \text{subject to} \quad & (1)\text{-}(22), (25)\text{-}(31) \end{aligned}$$

It is worth mentioning that the objective function of **SW** collects welfare of all participant buildings over the scheduling horizon $\mathcal{T}$. Taking the agreement constraints (29) and (31) into account, one may observe the zero-sum feature in the second term that $\sum_{i\in\mathcal{N}} \boldsymbol{\lambda}_{i,t}^{\mathrm{T}}\mathbf{e}_{i,t} = 0$ at each time slot $t \in \mathcal{T}$, and further simplify the objective function as $-\sum_{i\in\mathcal{N}}\sum_{t\in\mathcal{T}}\widetilde{C}_{i,t}$. However, distinguished from most of the existing works, the mutual payment term is explicitly presented in **SW**. This seemingly tedious handling is proved delicate in the subsequent sections.

3.3. Problem Decomposition and Decoupling with Pricing Scheme

Although **SW** can be solved by centralized optimization tools, this paper is aimed to design a fully distributed framework for privacy preservation. To this end, **SW** is split into N sub-problems to individual buildings that try to seek an optimal energy schedule solution by solving **P1**:

P1: Building's Optimization with Energy Sharing

$$\begin{aligned} \text{minimize} \quad & \sum_{t\in\mathcal{T}} \left(\widetilde{C}_{i,t} + \boldsymbol{\lambda}_{i,t}^{\mathrm{T}}\mathbf{e}_{i,t}\right) \\ \text{subject to} \quad & (1)\text{-}(20), (22), (25)\text{-}(31) \end{aligned}$$

However, **P1** cannot be solely solved for individual buildings as compared to **P0**. In fact, $\boldsymbol{\lambda}_{i,t}$ and $\mathbf{e}_{i,t}$ are variables coupled with neighboring buildings, as in (29) and (31).

In particular, let $\mathcal{E}$ collect all pairs (i, j) among N buildings, then $|\mathcal{E}| = N(N-1)/2$. As such, the coupling constraint (29) contains totally $|\mathcal{E}|$ equations at each time slot. Hence, (29) can be rewritten in a compact form:

$$\sum_{i\in\mathcal{N}} \mathbf{E}_i\mathbf{e}_{i,t} = \mathbf{0} \tag{33}$$

where $\mathbf{E}_i \in \mathbb{R}^{|\mathcal{E}|\times(N-1)}$ is a mapping matrix from nodes to lines. For a structure-fixed building community, the matrix $\mathbf{E}_i$ is considered as a known parameter and time-invariant. It is also obvious that $\mathbf{E}_i$ is sparse with $N-1$ elements 1, and remaining elements 0. For example, if the m-th row and j-th column element of $\mathbf{E}_i$ is 1, it means that the j-th node is a neighbor of i, and the link (i, j) locates as the m-th entry in the edge set $\mathcal{E}$.

Next, let $\boldsymbol{\lambda}_t := \{\lambda_{(i,j),t}\}_{(i,j)\in\mathcal{E}} \in \mathbb{R}^{|\mathcal{E}|}$ collect the Lagrangian dual variables associated with (33). Given this context, the elements of $\boldsymbol{\lambda}_t$ represent the marginal price of energy traded through the lines. It is thus fair for both buildings i and j to complete the energy sharing at the price $\lambda_{(i,j),t}$ at t-th time slot. Hence, a fair pricing scheme is devised in this paper as shown in (34):

$$\lambda_{i,t}^{j} = \lambda_{j,t}^{i} = \lambda_{(i,j),t}, \quad \forall (i, j) \in \mathcal{E}, \forall t \tag{34}$$

Furthermore, it is worth mentioning that the devised pricing scheme is aligned with peer-to-peer pairs, which motivates us to rewrite (34) in a compact form with the aid of $\mathbf{E}_i$:

$$\mathbf{E}_i^{\mathrm{T}} \boldsymbol{\lambda}_t = \boldsymbol{\lambda}_{i,t} \tag{35}$$

Plugging (35) into the objective function of **P1**, we can reformulate **P1** with the newly devised pricing scheme:

P2: Building's Optimization Problem Reformulation

$$\begin{aligned} \text{minimize} \quad & \sum_{t \in \mathcal{T}} \left(\widetilde{C}_{i,t} + \boldsymbol{\lambda}_t^{\mathrm{T}} \mathbf{E}_i \mathbf{e}_{i,t} \right) \\ \text{subject to} \quad & (1)\text{-}(20), (22), (25)\text{-}(28), (30) \end{aligned}$$

Here, we already relax the coupling constraints (29) and (31) by the proposed pricing scheme. Specifically, (29) is replaced by its KKT condition with the compact form in the objective function, while the price agreement (31) is replaced by the global variable $\{\boldsymbol{\lambda}_t\}_{t \in \mathcal{T}}$. Consequently, each building only needs to minimize its own cost as modeled in **P2**. However, the global variable $\{\boldsymbol{\lambda}_t\}_{t \in \mathcal{T}}$ inhibits the problem to be solved in a fully decentralized peer-to-peer manner. In addition, retaining dual variables in the problem brings challenges in dealing with the bilinear term $\boldsymbol{\lambda}_t^{\mathrm{T}} \mathbf{E}_i \mathbf{e}_{i,t}$. The detailed mathematical manipulation of these issues will be discussed in Section 4.

4. Proposed Decentralized Algorithm

In a distributed network, there are normally no central nodes or coordinators to gather and diffuse variables and relevant practical constraints. In consideration of this, a fully decentralized algorithm is proposed in this section.

4.1. Algorithm Design

As commented before, to devise a fully distributed algorithm for **P2**, challenges are to address the global variable $\boldsymbol{\lambda}_t$ and the bilinear term $\boldsymbol{\lambda}_t^{\mathrm{T}} \mathbf{E}_i \mathbf{e}_{i,t}$. In this regard, the conventional consensus ADMM is no longer applicable. Inspired by recent works in [30], we leverage dual-consensus ADMM (DC-ADMM) to address the arisen two challenges.

In **P2**, the primal variables are considered as local variables, and only the dual variables are exchanged between neighbors to reach a global pricing consensus. Specifically, each building $i \in \mathcal{N}$ holds a pricing estimate, i.e., $\boldsymbol{\lambda}_t^{(i)}$, of the global variable $\boldsymbol{\lambda}_t$. That is, $\boldsymbol{\lambda}_t^{(i)} := \{\lambda_{(i,j),t}^{(i)}\}_{(i,j) \in \mathcal{E}}$. With peer-to-peer communication network, each building i can receive estimates from neighbors, $\boldsymbol{\lambda}_t^{(j)}, j \in \mathcal{N}_i$. Upon receiving this neighboring information, the building i keeps the following constraints:

$$\hat{\boldsymbol{\lambda}}_t^{(i)} = \boldsymbol{\varepsilon}_{ij,t}, \tag{36}$$

$$\hat{\boldsymbol{\lambda}}_t^{(j)} = \boldsymbol{\varepsilon}_{ij,t}, \tag{37}$$

where the hat notation means the result from the latest iteration, and $\boldsymbol{\varepsilon}_{ij,t}$ is the slack variable. Let $\mathbf{u}_{ij,t}$ and $\mathbf{v}_{ij,t}$ be the dual variables associated with (36) and (37), the alternating update formula for these variables are given as follows:

$$\mathbf{u}_{ij,t} = \hat{\mathbf{u}}_{ij,t} + \frac{\rho}{2}\left(\hat{\boldsymbol{\lambda}}_t^{(i)} - \hat{\boldsymbol{\lambda}}_t^{(j)}\right) \tag{38a}$$

$$\mathbf{v}_{ij,t} = \hat{\mathbf{v}}_{ij,t} + \frac{\rho}{2}\left(\hat{\boldsymbol{\lambda}}_t^{(j)} - \hat{\boldsymbol{\lambda}}_t^{(i)}\right) \tag{38b}$$

where ρ is the given parameter. Note that $\boldsymbol{\varepsilon}_{ij,t}$ vanishes in (38) because of its closed form of the update (See Appendix 7). Hence, the update for primal and dual variables is in fact a minimax optimization problem, similar to the processes in formulating ADMM:

$$\begin{aligned} \min_{\{\boldsymbol{\lambda}_t^{(i)}\}} \max_{\{\mathbf{x}_{i,t},\mathbf{e}_{i,t}\}} \sum_{t\in\mathcal{T}} & \Big(-\widetilde{C}_{i,t} - \boldsymbol{\lambda}_t^{(i)\mathrm{T}}\mathbf{E}_i\mathbf{e}_{i,t} + \boldsymbol{\lambda}_t^{(i)\mathrm{T}}\hat{\mathbf{z}}_{i,t} \\ & + \rho\sum\nolimits_{j\in\mathcal{N}_i}\left\|\boldsymbol{\lambda}_t^{(i)} - (\hat{\boldsymbol{\lambda}}_t^{(i)} + \hat{\boldsymbol{\lambda}}_t^{(j)})/2\right\|^2\Big) \end{aligned} \tag{39}$$

where $\mathbf{x}_{i,t}$ denotes all local variables in the building i for clarity; $\mathbf{z}_{i,t}$ is defined in Appendix to represent the local auxiliary variable, as those in standard ADMM.

It is noticed that (39) is convex in $\{\boldsymbol{\lambda}_t^{(i)}\}_{t\in\mathcal{T}}$ given $\{\mathbf{x}_{i,t}, \mathbf{e}_{i,t}\}_{t\in\mathcal{T}}$ and concave in $\{\mathbf{x}_{i,t}, \mathbf{e}_{i,t}\}_{t\in\mathcal{T}}$ given $\{\boldsymbol{\lambda}_t^{(i)}\}_{t\in\mathcal{T}}$, so that the minimax theory is applicable here [30]. By completing the quadratic term, the primal, dual and auxiliary variables are respectively solved as follows, with the initial value from last iteration $\hat{\boldsymbol{\lambda}}_t^{(j)}$ and $\hat{\mathbf{z}}_{i,t}$.

Primal Variables Update

Each building i updates local primal variables in parallel:

$$\begin{aligned} \text{minimize} \quad & \sum_{t\in\mathcal{T}}\Bigg[\widetilde{C}_{i,t} + \frac{\rho}{4|\mathcal{N}_i|}\Bigg\|\frac{1}{\rho}\mathbf{E}_i\mathbf{e}_{i,t} - \frac{1}{\rho}\hat{\mathbf{z}}_{i,t} \\ & \quad + \sum\nolimits_{j\in\mathcal{N}_i}\left(\hat{\boldsymbol{\lambda}}_t^{(i)} + \hat{\boldsymbol{\lambda}}_t^{(j)}\right)\Bigg\|^2\Bigg] \\ \text{subject to} \quad & (1)\text{-}(20), (22), (25)\text{-}(28), (30) \\ \text{variables:} \quad & \{\mathbf{x}_{i,t}, \mathbf{e}_{i,t}\}_{t\in\mathcal{T}} \end{aligned} \tag{40}$$

where $|\mathcal{N}_i|$ is the number of neighbors of building $i \in \mathcal{N}$. Different from conventional ADMM, DC-ADMM keeps the primal variables in privacy that would not be transmitted.

Dual Variables Update

Upon attaining the local primal variables, each building updates the dual variable by the closed form in (41), and exchanges the result to neighboring buildings.

$$\boldsymbol{\lambda}_t^{(i)} = \frac{1}{2|\mathcal{N}_i|}\left[\sum_{j\in\mathcal{N}_i}\left(\hat{\boldsymbol{\lambda}}_t^{(i)} + \hat{\boldsymbol{\lambda}}_t^{(j)}\right) - \frac{1}{\rho}\hat{\mathbf{z}}_{i,t} + \frac{1}{\rho}\mathbf{E}_i\hat{\mathbf{e}}_{i,t}\right] \tag{41}$$

Auxiliary Variables Update

Upon receiving the neighboring information, each building updates the local auxiliary variable:

$$\mathbf{z}_{i,t} = \hat{\mathbf{z}}_{i,t} + \rho \sum\nolimits_{j\in\mathcal{N}_i} \left(\hat{\boldsymbol{\lambda}}_t^{(i)} - \hat{\boldsymbol{\lambda}}_t^{(j)}\right) \tag{42}$$

Algorithm 1 Proposed Fully Decentralized Algorithm

```
Initialize λ_t^(i), z_{i,t} = 0 for building i ∈ N; given parameter ρ; Set iteration k = 0;
repeat
    for Each building i ∈ N (in parallel) do
        Update primal variables x_{i,t}, e_{i,t} according to (40);
        Update dual variables λ_t^(i) according to (41);
        Transmit λ_t^(i) to neighboring buildings j ∈ N_i, and receive λ_t^(j) from neighbors;
        Update auxiliary variables z_{i,t} according to (42);
    end for
    k = k + 1;
until a predefined stopping criterion.
```

To be clearer, Algorithm 1 summarizes the proposed decentralized algorithm for **P2**. Note that the energy sharing profile and mutual payment are attained simultaneously by this holistic algorithm. In addition, the individual information privacy is preserved, since the only exchanged information are local estimates of global prices.

4.2. Advantages of the Proposed Framework and Algorithm

- *Generality.* In the proposed energy sharing model, the role of agents to be a producer or a consumer is endogenously determined. Unlike most existing works, the proposed model need not calculate the energy surplus or deficiency before conducting the energy sharing plans. Instead, the participants make communications with each other directly, in which they determined the energy sharing directions.

- *Optimality.* Due to the convexity and strong duality of **P1**, the solution of **P2** is identical to that of **P1**. Hence the reformulated problem is equivalent in term of final solution. In addition, instead of separately solving social welfare maximization problem and payment settling problem, a holistic framework is formulated to simultaneously deal with the energy sharing quantity and pricing scheme. This can lead to better solution quality with optimality guarantee.

- *Fairness.* The payments are integrated into the problem reformulation, in which per unit amount of shared energy shall be cleared according to its dual Lagrangian multiplier that economically represents the shadow price.

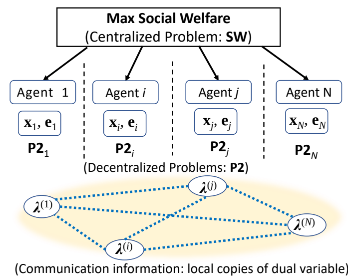


Figure 2: Problem structure and fully decentralized algorithm implementation.

As such, the proposed problem reformulation can provide a fair payment scheme, which is distinguished from most existing works dealing with the payment issues after the entire horizon.

- *Fully Decentralized.* The peer-to-peer energy sharing problem structure and the proposed fully distributed algorithm are illustrated in Fig. 2. As can be seen, the proposed algorithm avoids the need of coordinators at both the primal and dual variable updates in the iteration process, which suggests distinctive merits on high-level privacy protection as compared to most of the distributed optimization-based methods. We push one step forward to further decouple the problem by introducing local copies of pricing variables. In this context, the proposed framework can realize a fully decentralized real-world implementation without any central nodes to gather or diffuse information.

5. Numerical Simulations

To demonstrate the overall performance and effectiveness of the proposed energy sharing framework, numerical simulation results are reported in this section.

In the case study, a building community comprising four smart buildings is considered. The basic uncontrollable load data are extracted from SCE Dynamic Load Profiles[3], while HVAC units are considered as local controllable loads, with identical parameters given as follows: $G_i = 1.5\text{kWh}/°\text{C}$, $R_i = 1.33°\text{C}/\text{kWh}$, and $\eta_i = 0.15$, for all buildings $i \in \mathcal{N}$. The temperature discomfort coefficient β_i is set as $\{3.2, 3.6, 4, 4.4\}$. Utility line capacity is 200 kW, and energy sharing line capacity is 80kW. The energy sharing loss $\epsilon = 0.02$ for each link. Each building is assumed to have 20 EVs. The charging demand d_v^{EV} of the vehicles

[3]Southern California Edison. "SCE Dynamic Load Profiles,", https://www.sce.com/regulatory/load-profiles/dynamic-load-profiles.

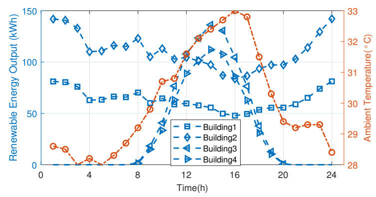


Figure 3: Renewable energy generation and outdoor temperature.

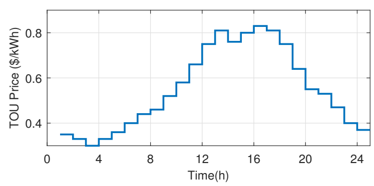


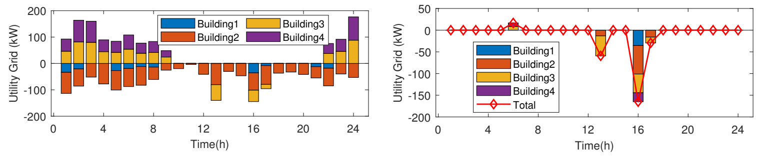
Figure 4: Time-of-use electricity price.

is estimated as per the daily travel mileage for the next trip and per mile energy consumption. According to the survey conducted by U.S. Department of Transportation Federal Highway Administration [31], a statistical probability method is conducted to analyze the travel behaviors, in which the mileage is subject to a logarithmic normal distribution function Log-$N(2.98,1,14^2)$, and the charging start/end time are generated randomly subject to truncated normal distribution with $N(8.92,3.2^2)$ and $N(17.6,3.4^2)$.

In addition, it is assumed that all buildings are equipped with BESS, and the energy level and charging/discharging power limited by $[20, 200]$ kWh and $[0, 50]$ kW, respectively. The self discharging, charging, discharging efficiency of BESS are $1, 0.95, 0.95$, and degradation cost is $\kappa_i^{\text{bat}} = 0.05\$/\text{kWh}$. The maximal state switching number is 3 per day. In the algorithm, the parameter $\rho = 4.5$ and the stopping criterion is both primal and dual residuals less than 0.02.

Fig. 3 shows the predicted solar, wind energy generation and outdoor temperature, based on the profiles on 15th June, 2020 from HK observatory. As shown in Fig. 3, buildings 1 and 2 are installed with wind turbines, while buildings 3 and 4 are installed with PV solar panels. It is noticed that the solar energy generation is during daytime while the wind energy generation is mostly at night. The utility energy purchasing price is shown in Fig. 4. The energy selling price is half of the purchasing price. All simulations are implemented using Yalmip with Gurobi on Matlab2021a on a personal computer.

Fig. 5 compares the utility energy purchasing profiles of four buildings with and without energy sharing. It shows that the purchasing energy is significantly reduced with energy sharing, facilitating the construction of 'net-zero energy building'. As in Fig. 5 (a), before energy sharing, building 1 and 2 (Wind buildings) have surplus energy to sell at most hours when wind energy supply is



(a) (b)

Figure 5: Utility grid power purchasing profiles. (a) Without energy sharing; (b) With energy sharing

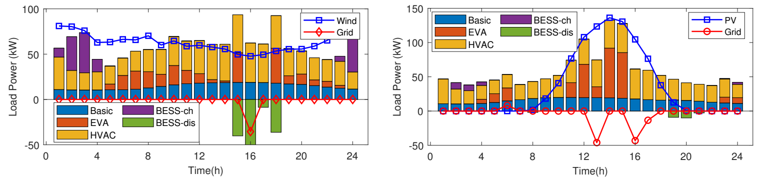
sufficient as compared to the local demand, while building 3 and 4 (PV buildings) are energy deficient. All of them can directly trade with the utility grid according to the TOU price. For example, PV buildings buy energy particularly in the midnight when the buying price is low while wind buildings sell more energy at 13-th and 16-hour when the selling price is relatively high.

However, after energy sharing, buildings would prefer neighboring buildings to exchanging the energy. In addition, it is interestingly observed in Fig. 5 (b) that the utility trading profiles tends to be similar after energy sharing. For instance, all buildings sell excessive energy during the net energy surplus time, e.g., at 13-th and 16-th hour. This observation demonstrates that the proposed framework can reach a re-dispatch consensus of building energies.

Specifically, Fig. 6 illustrates the energy management profiles of buildings after energy sharing. Building 1 and 3 are displayed due to space limit. As can be seen, the local loads including HVAC, BESS and EVs are flexibly controlled and balanced. Most importantly, the diversity of various renewable energy (e.g., PV, Wind) are explicitly observed in the local transaction market. For example, the wind building 1 has surplus energy at 1:00-9:00 and 20:00-24:00, while the building 3 are in shortage of energy supply in these periods, owing to the PV generation patterns. This leads to the motivation for buildings to energy sharing, as will be discussed.

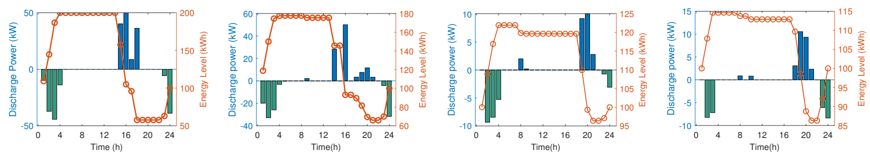
Fig. 7 and Fig. 8 show the energy level trajectory of BESS and EVA of four buildings. As is observed, the batteries are fully utilized to store excessive energy in wind buildings at first four hours, owing to the high level of wind power generation. Moreover, the battery energy level trajectories become almost identical after energy sharing. As such, the results suggest that the proposed framework can harmonize the distributed batteries efficiently by limited information exchange among buildings. In Fig. 8, the EVA charging requirements in four buildings are all met, and the trajectories are bounded by the dashed curves $E_{\min}^{\mathrm{EVA}}$ and $E_{\max}^{\mathrm{EVA}}$, which are calculated offline as per (12) and (13).

Fig. 9 displays the internal peer-to-peer trading profiles of each building pair over the schedule horizon. Compared with the neighboring energy importation profiles in Fig. 9 and the utility trading profiles in Fig. 5, buildings



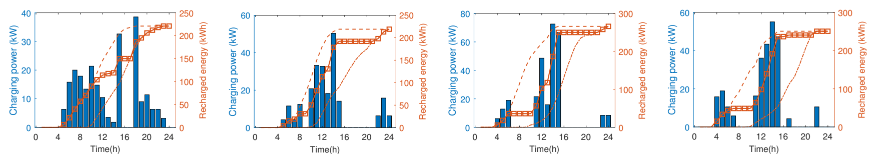
(a) Building 1 (b) Building 3

Figure 6: Energy management results after energy sharing.



(a) Building 1 (b) Building 2 (c) Building 3 (d) Building 4

Figure 7: Battery energy level trajectories.

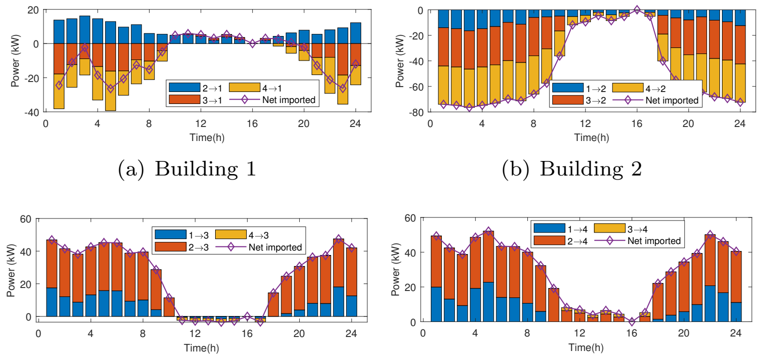


(a) Building 1 (b) Building 2 (c) Building 3 (d) Building 4

Figure 8: EVA charging power and energy trajectory.

prioritize neighbors when energy deficit or surplus exists after energy sharing. In particular, buildings 3 and 4 import energies from buildings 1 and 2 at night when wind energy generation exceeds the local demand. It is obvious to see the proactive trading between PV buildings and wind buildings, which proves the advantage of the proposed model in facilitating cooperative utilization of distributed renewable energies.

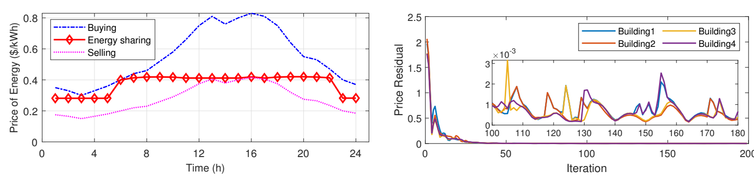
Fig. 10 plots the consensus sharing price as well as the convergence of pricing vector $\boldsymbol{\lambda}_t^{(i)}$ in each agent. It is noticed that the each building holds a local copy of the global shadow price vector,which are simultaneously determined along with energy quantities, in the proposed combined model. The energy sharing price profile is located below the buying price and above the selling price. This is reasonable since it is basically an incentive for buildings to participate in energy sharing; otherwise, they may opt to trade directly with the utility. In addition, it is observed that the resulting clearing price is time-varying, which implies a time-varying marginal sensitivity to energy trading of the building



(a) Building 1 (b) Building 2

(c) Building 3 (d) Building 4

Figure 9: Energy sharing profiles among all building pairs



(a) (b)

Figure 10: Energy sharing price. (a)The energy sharing consensus price profile; (b) The price residual in each building.

Table 1: Cost Comparison with and without Energy Sharing ($)

Metric	Bldg 1	Bldg 2	Bldg 3	Bldg 4
Total cost without ES	-26.34	-305.20	210.11	289.98
Local cost with ES	6.75	-21.65	-30.31	0.07
Payment to others	-52.99	-394.12	201.46	245.64
Total cost with ES	-46.24	-415.77	171.15	245.72
Cost reduction	19.9	110.57	38.96	44.26

community. Fig. 10 (b) demonstrates that the proposed algorithm converges at each buildings.

Table 1 presents the social cost of the smart building community with and without energy sharing. It is observed that energy sharing brings a significant cost reduction for all buildings, ranging from \$19.9 to \$110.57. From the row of mutual payment, it is clear to see that four buildings proactively settle the payments issues, e.g., $\boldsymbol{\lambda}_t^{(i)\mathrm{T}}\mathbf{E}_i\mathbf{e}_{i,t}$ in the proposed model, based on the energy sharing quantities in Fig 9 and the hourly price in Fig 10.

6. Conclusion

In this paper, we investigate the problem on peer-to-peer energy sharing among smart buildings by considering the dynamics of both BESS and EVs. A detailed energy sharing model is formulated in presence of the energy transmission loss. Instead of separately resolving energy trading and energy payment, the newly proposed framework can integrate the mutual payment into a combined optimization problem, which can effectively generate optimal pricing scheme. In addition, a fully decentralized algorithm based on modified version of ADMM is developed to reach the global pricing consensus, which can preserve the privacy of participant buildings to a significant extent. Numerical case studies demonstrate the effectiveness of the proposed framework and suggest a high potential of practical application in facilitating a zero-emission building community.

7. Appendix: Proof for the updates of distributed algorithm

Proof. By leveraging standard ADMM, dual variables are the updated as follows:

$$\begin{aligned} \mathbf{u}_{ij,t} &= \hat{\mathbf{u}}_{ij,t} + \rho(\hat{\boldsymbol{\lambda}}_t^{(i)} - \boldsymbol{\varepsilon}_{ij,t}) \\ \mathbf{v}_{ij,t} &= \hat{\mathbf{v}}_{ij,t} + \rho(\hat{\boldsymbol{\lambda}}_t^{(j)} - \boldsymbol{\varepsilon}_{ij,t}) \end{aligned} \tag{43}$$

Then the update for slack variables is to solve the problem:

$$\begin{aligned} \text{minimize} \quad & \hat{\mathbf{u}}_{ij,t}^{\mathrm{T}}(\hat{\boldsymbol{\lambda}}_t^{(i)} - \boldsymbol{\varepsilon}_{ij,t}) + \hat{\mathbf{v}}_{ij,t}^{\mathrm{T}}(\hat{\boldsymbol{\lambda}}_t^{(j)} - \boldsymbol{\varepsilon}_{ij,t}) \\ & + \frac{\rho}{2}\|\hat{\boldsymbol{\lambda}}_t^{(i)} - \boldsymbol{\varepsilon}_{ij}\|^2 + \frac{\rho}{2}\|\hat{\boldsymbol{\lambda}}_t^{(j)} - \boldsymbol{\varepsilon}_{ij,t}\|^2 \\ \text{variables:} \quad & \boldsymbol{\varepsilon}_{ij,t} \end{aligned} \tag{44}$$

The closed form solution of (44) is given by:

$$\boldsymbol{\varepsilon}_{ij,t} = \frac{1}{2}(\hat{\boldsymbol{\lambda}}_t^{(i)} + \hat{\boldsymbol{\lambda}}_t^{(j)}) + \frac{1}{2\rho}(\hat{\mathbf{u}}_{ij,t} + \hat{\mathbf{v}}_{ij,t}) \tag{45}$$

Plugging (45) into (43), they are updated as follows:

$$\begin{aligned} \mathbf{u}_{ij,t} &= \hat{\mathbf{u}}_{ij,t} + \frac{\rho}{2}(\hat{\boldsymbol{\lambda}}_t^{(i)} - \hat{\boldsymbol{\lambda}}_t^{(j)}) - \frac{1}{2}(\hat{\mathbf{u}}_{ij,t} + \hat{\mathbf{v}}_{ij,t}) \\ \mathbf{v}_{ij,t} &= \hat{\mathbf{v}}_{ij,t} + \frac{\rho}{2}(\hat{\boldsymbol{\lambda}}_t^{(j)} - \hat{\boldsymbol{\lambda}}_t^{(i)}) - \frac{1}{2}(\hat{\mathbf{u}}_{ij,t} + \hat{\mathbf{v}}_{ij,t}) \end{aligned} \tag{46}$$

To further simplify the update formula, it is observed in (46) that, $\mathbf{u}_{ij,t}[k] + \mathbf{v}_{ij,t}[k] = 0$ holds for every iteration k, if initialized with $\mathbf{u}_{ij,t}[0] + \mathbf{v}_{ij,t}[0] = 0$. Hence, the update for $\boldsymbol{\varepsilon}_{ij,t}$ is integrated into $\mathbf{u}_{ij,t}$ and $\mathbf{v}_{ij,t}$, of which the updates are shown in (38a) and (38b).

Moreover, (45) is accordingly simplified as follows:

$$\boldsymbol{\varepsilon}_{ij,t} = \frac{1}{2}(\hat{\boldsymbol{\lambda}}_t^{(i)} + \hat{\boldsymbol{\lambda}}_t^{(j)}) \tag{47}$$

By observing the structures of (38) and (47), we have the following equalities by symmetry for j of each pair $(i,j) \in \mathcal{E}$:

$$\boldsymbol{\varepsilon}_{ij,t} = \boldsymbol{\varepsilon}_{ji,t}, \qquad \mathbf{u}_{ij,t} = -\mathbf{u}_{ji,t} = \mathbf{v}_{ji,t} \tag{48}$$

Let $\mathbf{z}_{i,t} = 2\sum_{j\in\mathcal{N}_i}\mathbf{u}_{ij,t} = \sum_{j\in\mathcal{N}_i}(\mathbf{u}_{ij,t}+\mathbf{v}_{ji,t})$, we have the minimax problem and update formula as in (39)-(42). $\square$

8. Acknowledge

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