Energy Trading in Microgrids for Synergies among Electricity, Hydrogen and Heat Networks

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Abstract

In this paper, an energy trading mechanism among microgrids is introduced to incentive them to share extra electricity, in order to balance renewable energy generation and energy demand at a low cost. However, energy trading might not completely absorb the excess renewable energy, a multi-energy management framework including fuel cell vehicles, energy storage, combined heat and power (CHP) and renewable energy is proposed, and the characteristics and scheduling arrangements of fuel cell vehicles are considered to further realize the local absorption of renewable energy and enhance the economic benefits of microgrids. This work designs a joint energy scheduling and trading algorithm based on Lyapunov optimization and double auction to solve the optimization problem of microgrids, which guarantees the truthfulness of information, customers satisfaction and optimal benefits. The simulations based on real data evaluate the performance of the multi-energy management framework and demonstrate the effectiveness of the proposed algorithm.

Keywords: Energy trading, energy storage, Lyapunov optimization, double auction

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1. Introduction

Traditional power grid consumes fossil fuel to generate electricity and transmits electricity over long distance, which results in quick depletion of fossil fuel resources and serious environmental pollution. This motivates the study of distributed microgrids, which can efficiently realize investment deferral [1], local balance [2], resiliency advancement [3], security reinforcement [4] and reduce greenhouse gas emissions and energy losses by using renewable energy source [5-7]. However, the renewable energy generation is stochastic which may influence the energy reliability and quality. Meanwhile, considering the heat demands of users, the combined heat and power (CHP) which can efficiently generate both electricity and heat simultaneously by consuming natural gas is introduced. Also, energy storage plays a key role in improving energy reliability by storing extra energy to be used in future. However, it is not efficient and economic for individual microgrid to serve its users due to the mismatch of renewable energy generation and electricity demand.

Geographically-distributed microgrids can improve energy reliability and efficiency by sharing energy. However, microgrid is selfish, and wants to minimize its own cost for sharing energy. Only if its benefit can not be lower than the one without cooperation in any case, can a microgrid be incentivized to join energy trading. This needs an effective method to carry out energy scheduling and trading among microgrids, to achieve benefit maximization for individual microgrids. Several inter-related decisions are involved: (1) Energy pricing: what method should be adopted for energy sale and purchase among microgrids, and at what prices? (2) Energy scheduling: with time-varying demand and renewable generation of each microgrid, should a microgrid serve the demand using its energy storage or trading with other microgrids? When local energy storage and energy trading cannot satisfy the demand, should a microgrid serve the demand by CHP or purchasing energy from utility companies, to exploit time-varying electricity prices? These decisions should optimally and efficiently made online, while guaranteeing individual microgrid’s benefits for a long period. Therefore,
a joint algorithm for energy scheduling and trading for microgrids is designed. A double-auction based method is proposed to determine the purchase price and selling price, increase economic benefits of microgrids, and ensure the truthfulness of the information that microgrids submit in energy trading.

However, due to the limitation of battery storage, the microgrid might not fully exploit the time-diversity of renewable energy generation. In order to improve the utilization of renewable energy generation, we can introduce hydrogen into microgrid and excess renewable energy can be used to electrolyze water to produce and store hydrogen in hydrogen storage tanks. Fuel cell vehicles can convert hydrogen into electricity to supply the microgrid when the microgrid is short of energy, and fuel cell vehicles can be used for transportation. The following few advantages contain the reasons we introduce hydrogen: Firstly, for the same size of energy storage, hydrogen storage can provide larger amounts of energy than battery and can be filled in a few minutes. A number of facilities, which integrate renewable energy and energy storage, are under operation all over the world and most of them use hydrogen for energy storage in both stand-alone and grid-tied power generation systems [8, 9]. In these facilities, the hydrogen storage system is often coupled with a battery bank for short-term energy storage, thus achieving a hybrid poly-generation system. A proper integration of hydrogen storage systems and batteries increases bus stability and enhances the management of intermittent power peaks and transient loads [10]. Secondly, the whole electricity-hydrogen conversion process only utilizes water and is carbon free. Last but not least, hydrogen can be purchased from a hydrogen-producing company and used to the transportation of fuel cell vehicles. Fuel cell vehicles are particularly suited to provide spinning reserves and peak power to the grid [11, 12]. In contrast to plug-in electric vehicles, fuel cell vehicles can be operated continuously and have very low emissions [11]. Hydrogen, as a clean energy with high calorific value, is attracting wide attention. Therefore, the Car as Power Plant (CaPP) [13] is presented to introduce a controllable energy system, which uses fuel cell vehicles as dispatchable power plants [14]. Considering the average driving time of vehicles are less than 10%
of the whole day, vehicles can generate electricity by combusting hydrogen in a cleaner way than other power system when they are parked, and there is a huge potential for fuel cell vehicles to take place of traditional power plants or reduce the number of new plants in the future. Therefore, the synergies between hydrogen and electricity can be explored to increase the benefits of microgrids.

In particular, main contributions of this paper are as follows:

- A multi-energy management framework including fuel cell vehicles, energy storage, CHP and renewable energy is proposed. The synergies between hydrogen and electricity can further realize the local absorption of excess renewable energy and improve the economic benefits of microgrids.

- A joint energy scheduling and trading algorithm based on Lyapunov optimization and double auction is designed to solve the optimization problem of microgrids which can guarantee that no microgrid will decrease benefit by energy trading.

- Through theoretical analysis, the proposed algorithm can achieve better trade-off among energy trading cost, energy storage and users’ satisfaction. Moreover, by using practical data sets, the effectiveness of the proposed algorithm is verified.

In the rest of paper, Section II introduces the related works. Section III describes the system model and cost functions. Then, Section IV proposes a joint algorithm based on Lyapunov optimization and double auction for the energy scheduling and trading problem, and proves the theoretical performance of this algorithm. Section V shows numerical results and Section VI concludes the paper.

2. Related Works

Energy sharing is a way to reduce the unbalance of supply and demand of microgrids, and improve the local consumption of renewable energy. A number
of research efforts have been conducted. In [15], energy sharing allows participants to exchange energy in order to lower reliance on the utility company. In [16], development of peer to peer energy sharing has significant advantage to benefit the prosumers in both earning revenues and reducing energy cost. In [17], because of the stochastic renewable energy generation, the nanogrids form a nanogrid cluster to share renewable energy. In [18], a real-time demand response model is presented to assist the energy sharing provider, which realizes the maximization of energy sharing provider’s utility. In [19], energy trading and sharing schemes for multiple hubs increase system flexibility and reduce the cost of system.

However, owing to the randomness of renewable energy, it is difficult to schedule the renewable energy sharing among microgrids, and investigate the primary problem on economics. There are two kinds of market based models that are applicable for resource management of energy sharing. The first one is the market model where resource owners decide the price based on users’ demands by game approach. For the first situation, two different models are proposed: 1) the prosumers decide the price of energy together [20–22]; 2) a leader-follower structure decides the price [23–25]. Liu et al. [20] formulate a dynamical internal pricing model for energy sharing of prosumers who decide the price of energy. Lu et al. [21] establish an informative game vector to perform price-based energy interactions among microgrids who decide the price. Chen et al. [22] propose a novel energy sharing game in prosumers to determine the role of buyer or seller and the sharing price. Liu et al. [23] propose a Stackelberg game approach, where the microgrid operator acts as the leader and prosumers act as the followers to decide the price together. Tushar et al. [24] formulate a non-cooperative Stackelberg game, to capture the interaction between the shared facility controller and the residential units who decide the price of energy to minimize the cost. Motalleb et al. [25] propose a networked Stackelberg competition among firms to determine their optimal bids for price of a market transaction. The second one is the auction model where every player acts independently and agrees privately on the price. According to the
type of interactions between buyers and sellers, auction can be divided into two classes, one-side auction \[26\] and two-side auction \[27,30\]. Auction mechanism helps the players benefit from cooperation and energy trading with little global information. And auction mechanism can make every player to share the energy autonomously and guarantee the truthfulness of information. Therefore, an auction mechanism is used to determine the price of energy sharing in this paper.

Energy storage and CaPP are also effective ways to reduce the unbalance of supply and demand of microgrids, and improve the local consumption of renewable energy. In \[31\], Huang et al. develop a low-complexity algorithm with energy storage management to minimize the average cost of a power consuming entity. In \[32\], Gatzianas et al. explicitly take actual energy storage into account, and construct an algorithm for energy management by Lyapunov optimization technique. In \[33\], Gayme et al. investigate distributed energy storages and illustrate their effects using an example along with time-varying demand profiles. In \[34\], Good et al. propose an aggregation modeling method for multi-energy conversion, storage and demand to exploit distributed energy flexibility and provide multiple services.

The scheduling of the vehicles and electrolyzers are the main aspects to be considered in the operational control of CaPP microgrid. Centralized optimization approaches such as minimizing operating costs \[35\] or power losses \[36\], are used to address the scheduling problem of vehicles. In \[37\], the scheduling problem in the microgrid among renewable energy sources (RES), electrolyzer and vehicle-to-grid (V2G) power is to minimize the power purchased from the grid. In \[38\] and \[39\], there are some optimization methods to schedule the operation of electrolyzers. In \[40\], the electrolyzer levels out voltage fluctuations in a weak grid and improves the power quality of microgrid based on a dynamic electrolyzer model.

However, the existing works do not consider the coordinated operation and multi-energy demand of multiple microgrids after introducing hydrogen storage and fuel cell vehicles. In this paper, a multi-energy management framework
including fuel cell vehicles, energy storage, CHP and renewable energy is proposed, which can further realize the local absorption of renewable energy, yield complementarity among multiple energy and enhance the economic benefits of microgrids. A joint energy scheduling and trading algorithm based on Lyapunov optimization and double auction is designed to solve the optimization problem of microgrids. The implementation of the algorithm only depends on current system states without knowing any priori information, and microgrids have to guarantee the truthfulness of information about energy to minimize the operating cost. In the end, the performance of the proposed mechanism is verified.

3. System Model

A system is considered consisting of $n$ interconnected microgrids, an electricity utility company, a gas utility company and a hydrogen-producing company. Each microgrid is equipped with renewable energy, CHP, fuel cell vehicles, battery, hydrogen storage, boiler and water tank as shown in Fig.1. Microgrids can harvest renewable energy such as wind and solar power. Fuel cell vehicles can generate electricity by consuming hydrogen. CHP can consume natural gas to generate electricity, and at the same time, the generated heat follows its electricity production with fixed ratios. In addition, each microgrid can store extra energy for the demand in future.

3.1. Energy Purchase

Microgrid $i$ harvests $N_i(t)$ units of energy generated by renewable energy during one time slot $t$. Here one time slot is set to be one hour in order to coordinate with simulation. The electricity utility company uses fossil energy to generate electricity, so it has huge energy generation at one time slot which means any constraints on energy generation of the electricity utility company are not considered. The same assumption is applied to the gas utility company and hydrogen-producing company). Microgrid $i$ purchases $E_i(t)$ units of energy from the electricity utility company with price $p_e(t)$. From the gas utility
Fig. 1. Energy flows of system
company, microgrid \( i \) purchases \( P_{CHP}^i(t) \) and \( H_{CHP}^i(t) \) units of gas to generate \( \eta_{pg} P_{CHP}^i(t) \) units of electricity and \( \eta_{hg} H_{CHP}^i(t) \) units of hot water by CHP at time slot \( t \). \( \eta_{pg} \) and \( \eta_{hg} \) are the conversion efficiency of CHP from natural gas to electricity and heat respectively. Moreover, microgrid \( i \) purchases \( H_b^i(t) \) units of gas to produce \( \eta_{bg} H_b^i(t) \) units of hot water by boiler at time slot \( t \). \( \eta_{bg} \) is the conversion efficiency of boiler from natural gas to heat. The price of gas is \( p_g(t) \). When there is not enough hydrogen for fuel cell vehicles, microgrid \( i \) will purchase \( d_i(t) \) units of hydrogen from the hydrogen-producing company with price \( p_y(t) \).

3.2. Energy Demands

Microgrid \( i \) needs to meet electricity \( L_{ie}(t) \), hydrogen \( L_{iy}(t) \) and heat \( L_{ih}(t) \) demands. Although these demands are stochastic, they still need to be met quickly and precisely.

3.2.1. Electricity Demands

Firstly, microgrid \( i \) uses renewable energy to meet its users’ electricity demands \( L_{ie}(t) \). If \( N_i(t) > L_{ie}(t) \), extra renewable energy can be used for energy storage, water electrolysis and energy trading. Otherwise, microgrid \( i \) uses all renewable energy to serve its loads. The unsatisfied electricity loads are expressed as \( L_{ie}(t) - N_i(t) \) and are served by the following methods:

- **Discharge the battery.** Microgrid \( i \) can draw \( D_{ie}(t) \) units of electricity from battery to serve unsatisfied electricity loads.

- **Generate electricity by hydrogen.** Fuel cell vehicles can use hydrogen to generate \( \eta_f hY_{if}(t) \) units of electricity.

- **Generate electricity by CHP.** CHP can consume natural gas to generate \( \eta_{pg} P_{CHP}^i(t) \) units of electricity to meet electricity demands.

- **Purchase electricity by energy trading.** Microgrid \( i \) may acquire \( X_i(t) \) units of electricity by trading with other microgrids.
• Purchase electricity from the electricity utility company. Microgrid \( i \) can purchase \( E_i(t) \) units of electricity from the electricity utility company.

3.2.2. Hydrogen Demands

Firstly, vehicle \( l_i \) uses \( Y_{il}(t-1) \) units of hydrogen stored in the vehicle to meet its driving demands \( h_{il}(t) \), which can be estimated by historical data. If \( Y_{il}(t-1) > h_{il}(t) + Y_{il,min} \), the vehicle can drive normally. If \( Y_{il}(t-1) \leq h_{il}(t) + Y_{il,min} \), vehicle \( l_i \) uses all hydrogen in the vehicle for driving. The deficient hydrogen is obtained from microgrid \( i \) or purchased from the hydrogen-producing company. Microgrid \( i \) purchases \( d_i(t-1) \) units of hydrogen to meet total hydrogen demands \( L_{iy}(t) \) of all vehicles at time slot \( t \).

3.2.3. Heat Demands

Microgrid \( i \) uses the hot water stored in the water tank to meet its heat demands. If these water cannot meet its heat demands, microgrid \( i \) will use both CHP and boiler to produce \( \eta_{bg} H_{CHP}^i(t) + \eta_{bg} H_b^i(t) \) units of hot water to meet its heat demands \( L_{ih}(t) \) at time slot \( t \).

3.3. Dynamic Model for the Energy Storages

Each microgrid has a battery which can store extra electricity generated by renewable energy generation, and a hot water tank to supply hot water. Meanwhile, the hydrogen storage is introduced and the dynamic model for the three kinds of energy storages is considered. For microgrid \( i \), the electricity of the battery, hydrogen of the storage and equivalent thermal energy of the hot water tank are \( B_i(t) \), \( Y_i(t) \) and \( W_i(t) \) respectively at the end of one time slot. The electricity, hydrogen and equivalent thermal energy are charged in the amount of \( C_{cie}(t), C_{cyi}(t) \) and \( C_{che}(t) \), and discharged in the amount of \( D_{cie}(t), D_{cyi}(t) \) and \( D_{che}(t) \) respectively. Then the energy storage dynamics can be obtained by:

\[
B_i(t + 1) = B_i(t) + C_{cie}(t) - D_{cie}(t) \tag{1}
\]

\[
Y_i(t + 1) = Y_i(t) + C_{cyi}(t) - D_{cyi}(t) \tag{2}
\]
\[ W_i(t + 1) = W_i(t) + C_{ih}(t) - D_{ih}(t) \]  

where \( C_{iy}(t) \) injected into hydrogen storage is generated by electrolyzer during one time slot. \( \frac{h C_{iy}(t)}{\eta_e} \) is the energy consumed by electrolyzer during one time slot, \( \eta_e \) is the conversion efficiency of electrolyzer from electricity to hydrogen, \( h \) is the heating value of hydrogen which is 3.509 kWh/Nm\(^3\). Hydrogen needs to be compressed and stored. The compression energy is \( c_1 C_{iy}(t) \), and \( c_1 \) is the specific energy consumption of compressor. To be specific, the battery, hydrogen storage and hot water tank have a lot of constraints. Firstly, electricity charging and discharging will not happen simultaneously:

\[ 1_{C_{ie}(t) > 0} + 1_{D_{ie}(t) > 0} \leq 1 \]  

\[ 1_{f(x) > 0} = \begin{cases} 
1 & \text{if } f(x) > 0 \\
0 & \text{otherwise} 
\end{cases} \]

Battery, hydrogen storage and water tank have finite capacities:

\[ 0 \leq B_i(t) \leq B_{i,max} \]  

\[ 0 \leq Y_i(t) \leq Y_{i,max} \]  

\[ 0 \leq W_i(t) \leq W_{i,max} \]  

where \( B_{i,max}, Y_{i,max} \) and \( W_{i,max} \) are the upper bounds of battery, hydrogen storage and hot water tank’s thermal energy. There are maximum electricity, hydrogen and equivalent thermal energy charging \( C_{ie,max}, C_{iy,max}, C_{ih,max} \) and discharging \( D_{ie,max}, D_{iy,max}, D_{ih,max} \) during one time slot. Thus, the charging and discharging constraints of energy storage are denoted by:

\[ 0 \leq C_{ie}(t) \leq C_{ie,max}, 0 \leq D_{ie}(t) \leq D_{ie,max} \]  

\[ 0 \leq C_{iy}(t) \leq C_{iy,max}, 0 \leq D_{iy}(t) \leq D_{iy,max} \]  

\[ 0 \leq C_{ih}(t) \leq C_{ih,max}, 0 \leq D_{ih}(t) \leq D_{ih,max} \]
The feasible control decision on $C_{ie}(t), D_{ie}(t)$ should ensure the constraints (4), (5) and (8) are satisfied simultaneously. Since electricity charging and discharging will not happen simultaneously, the energy level of battery cannot exceed the capacity of battery, which means $B_i(t) + C_{ie}(t) \leq B_i,\text{max}$. Meanwhile, the energy level of battery cannot be lower than 0, which means $B_i(t) - D_{ie}(t) \geq 0$. Therefore, the charging and discharging constraints of the battery are denoted by:

$$0 \leq C_{ie}(t) \leq \min[B_i,\text{max} - B_i(t), C_{ie,\text{max}}]$$  \hspace{1cm} (11)

$$0 \leq D_{ie}(t) \leq \min[B_i(t), D_{ie,\text{max}}]$$  \hspace{1cm} (12)

### 3.4. Dynamic Model for the Fuel Cell Vehicles

Because the fuel cell vehicles can act as controllable power plant, the fuel cell vehicles are introduced and the dynamic model for the fuel cell vehicles is considered. The model includes the transportation features and the power generation of the fuel cell vehicles. The transportation features are the information about the departure, arrival time and driving distance of each vehicle, which can be estimated. The power generation is determined by the transportation features and hydrogen storage of vehicles. The hydrogen in the vehicle $l_i$ is $Y_{il}(t)$ at the end of one time slot. The number of vehicles in the microgrid $i$ is $L_i$. Then the model of fuel cell vehicle $l_i$ is as follows:

$$Y_{il}(t + 1) = \begin{cases} 
Y_{il}(t) + D_{iyl}(t) + d_{il}(t) & \text{injecting} \\
Y_{il}(t) - Y_{ifl}(t) & \text{generation} \\
Y_{il}(t) - h_{il}(t) & \text{driving}
\end{cases}$$  \hspace{1cm} (13)

$$\sum_{l=1}^{L_i} D_{iyl}(t) = D_{iy}(t); \sum_{l=1}^{L_i} d_{il}(t) = d_i(t)$$  \hspace{1cm} (14)

$$\sum_{l=1}^{L_i} Y_{ifl}(t) = Y_{if}(t); \sum_{l=1}^{L_i} h_{il}(t) = h_i(t)$$

$$h_{il}(t) = \eta_d h_{i\text{ld}(t)}$$  \hspace{1cm} (15)
The model of (13) is a hybrid piece affine model with three modes. The injecting mode denotes that the vehicle is being injected. The generation mode represents that the vehicle is available for power generation. The driving mode denotes that the vehicle is driving. The three modes will not happen simultaneously. \( D_{iyl}(t) + d_{il}(t) \) is the hydrogen injected into vehicle \( l_i \) at time slot \( t \). The fuel cell vehicle \( l_i \) obtains hydrogen \( D_{iyl}(t) \) from the microgrid \( i \) and purchases hydrogen \( d_{il}(t) \) from the hydrogen station of the hydrogen-producing company. \( Y_{iff}(t) \) is the hydrogen consumed for generation by vehicle \( l_i \) at time slot \( t \). The power generated by fuel cell vehicle \( l_i \) is denoted as \( \eta_f Y_{iff}(t) \), where \( \eta_f \) is the conversion efficiency of the fuel cell from hydrogen to electricity. \( h_{il}(t) \) is the hydrogen used for transportation by vehicle \( l_i \) at time slot \( t \), \( h_{il}(t) \) is the travel distance, and \( \eta_d \) is the hydrogen that each vehicle consumes per kilometre. For fuel cell vehicle \( l_i \), there are maximum hydrogen storage \( Y_{il,\text{max}} \), hydrogen injected \( D_{iyl,\text{max}} \) and \( d_{il,\text{max}} \), hydrogen consumed for generation \( Y_{iff,\text{max}} \) and hydrogen used for transportation \( h_{il,\text{max}} \) during one time slot:

\[
0 \leq Y_{il}(t) \leq Y_{il,\text{max}} \tag{16}
\]

\[
0 \leq D_{iyl}(t) \leq D_{iyl,\text{max}}, 0 \leq d_{il}(t) \leq d_{il,\text{max}} \tag{17}
\]

\[
0 \leq Y_{iff}(t) \leq Y_{iff,\text{max}} \tag{18}
\]

\[
0 \leq h_{il}(t) \leq h_{il,\text{max}} \tag{19}
\]

3.5. Cost Function

The cost function of microgrid \( i \) consists of the payment and revenue which is denoted as

\[
C_i(t) = C_{ihy}(t) + C_{ip}(t) + C_{ig}(t) + C_{iX}(t) - R_{iS}(t) - R_{ip}(t) \tag{20}
\]
\[ C_{ihy}(t) = p_y(t)d_i(t), \quad C_{ip}(t) = E_i(t)p_e(t) \]
\[ C_{ig}(t) = (P_i^{CHP}(t) + H_i^{CHP}(t) + H_i^b(t))p_y(t) \]
\[ C_{iX}(t) = \beta_i(t)X_i(t), \quad R_{iS}(t) = \alpha_i(t)S_i(t), \quad R_{ip}(t) = E_{io}(t)p_{eo}(t) \]

where \( C_{ihy}(t) \) is the hydrogen cost of purchasing hydrogen from the hydrogen-producing company by all vehicles of microgrid \( i \) at time slot \( t \). \( C_{ip}(t) \) and \( C_{ig}(t) \) are the costs of purchasing electricity and gas from the electricity and gas utility company at time slot \( t \). \( C_{iX}(t) \) and \( R_{iS}(t) \) are the cost of purchasing electricity from other microgrids and the revenue of selling electricity to other microgrids in energy trading at time slot \( t \). \( R_{ip}(t) \) is the revenue of selling electricity to the electricity utility company at time slot \( t \). \( p_y(t) \) is the hydrogen price of the hydrogen-producing company. \( d_i(t) \) is the amount of hydrogen purchased from the hydrogen-producing company by all vehicles of microgrid \( i \) at time slot \( t \). \( E_i(t) \) is the amount of electricity purchased from the electricity utility company by microgrid \( i \) at time slot \( t \). When microgrid \( i \) purchases electricity from other microgrids, \( \beta_i(t) \) is the purchase price and \( X_i(t) \) is the amount of electricity at time slot \( t \). When microgrid \( i \) sells electricity to other microgrids, \( \alpha_i(t) \) is the selling price of microgrid \( i \) and \( S_i(t) \) is the amount of electricity at time slot \( t \). \( E_{io}(t) \) and \( p_{eo}(t) \) are the amount and price of electricity sold to the electricity utility company by microgrid \( i \) at time slot \( t \).

Note that the electricity demand \( L_{ie}(t) \), hydrogen demand \( L_{iy}(t) \) and heat demand \( L_{ih}(t) \) of microgrid \( i \) should be satisfied when they arrive, i.e.:

\[
L_{ie}(t) = E_i(t) + N_i(t) + X_i(t) - S_i(t) - C_{ie}(t) + D_{ie}(t) + \eta_f hY_{jf}(t) - \frac{hC_{iy}(t)}{\eta_e} - c_1 C_{ip}(t) + \eta_{pg} P_i^{CHP}(t) - E_{io}(t) \]
\[ L_{iy}(t) = h_i(t) \]
\[ L_{ih}(t) = \eta_{hg} H_i^{CHP}(t) + \eta_{hg} H_i^b - C_{ih}(t) + D_{ih}(t) \]
4. Solution Methodology

4.1. Optimization Method

The strategy set of microgrid \( i \) is \( M_i(t) = \{ C_{ie}(t), D_{ie}(t), C_{iy}(t), D_{iy}(t), C_{ih}(t), D_{ih}(t), D_{iyd}(t), d_{il}(t), Y_{i,fl}(t), h_{il}(t), E_i(t), P_{CHP}^i(t), H_{CHP}^i(t), H_{h}^i(t), X_i(t), S_i(t), E_{io}(t) \} \). According to the system model, the optimization problem of microgrid \( i \) is to find a control policy which schedules the electricity, hydrogen and heat at each time slot to minimize the time average energy cost, which can be denoted as the stochastic network optimization problem:

\[
\min_{M_i(t)} \lim_{T \to \infty} \frac{1}{T} \sum_{t=1}^{T} E\{C_i(t)\} \tag{23}
\]

subject to (1) - (19), (22).

The Lyapunov optimization gives simple online solutions based on the current information of system state as opposed to the traditional approaches like Markov decision processes and dynamic programming which have very high computation complexity and require a-priori information of all the random processes in the system, and the performance of Lyapunov optimization algorithm can be close to the optimal value arbitrarily [41]. The underlying assumption about availability of future information renders offline approaches ill-suited for energy storage system applications with high uncertainty, whereas dynamic programming solutions are impractical for multiple networked energy storage system [42]. The time average expected values under any feasible control policy
of original problem are denoted as follows:

$$C_{ie} = \lim_{T \to \infty} \frac{1}{T} \sum_{t=1}^{T} \mathbb{E}\{C_{ie}(t)\}, \quad D_{ie} = \lim_{T \to \infty} \frac{1}{T} \sum_{t=1}^{T} \mathbb{E}\{D_{ie}(t)\}$$

$$C_{iy} = \lim_{T \to \infty} \frac{1}{T} \sum_{t=1}^{T} \mathbb{E}\{C_{iy}(t)\}, \quad D_{iy} = \lim_{T \to \infty} \frac{1}{T} \sum_{t=1}^{T} \mathbb{E}\{D_{iy}(t)\}$$

$$C_{ih} = \lim_{T \to \infty} \frac{1}{T} \sum_{t=1}^{T} \mathbb{E}\{C_{ih}(t)\}, \quad D_{ih} = \lim_{T \to \infty} \frac{1}{T} \sum_{t=1}^{T} \mathbb{E}\{D_{ih}(t)\}$$

$$\overline{D_{iyl}} + \overline{d_{il}} = \lim_{T \to \infty} \frac{1}{T} \sum_{t=1}^{T} \mathbb{E}\{D_{iyl}(t) + d_{il}(t)\}$$

$$\overline{Y_{ifl}} + \overline{h_{il}} = \lim_{T \to \infty} \frac{1}{T} \sum_{t=1}^{T} \mathbb{E}\{Y_{ifl}(t) + h_{il}(t)\}$$

(24)

The above stochastic network optimization problem (23) cannot be solved directly due to the capacity constraints of the battery, hydrogen storage and water tank (5) - (7) of microgrid \(i\) and hydrogen storage (16) of fuel cell vehicle \(l\). To be specific, stochastic network optimization can ensure that the average energy consumption equals the average energy generation for a long period, but cannot provide a hard constraint on the difference between the consumption and generation at any time slot. In order to solve the issue, the problem is relaxed, which is stated as follows. The optimization problem (23) is subject to:

$$C_{ie} = \overline{D_{ie}}$$

$$C_{iy} = \overline{D_{iy}}$$

$$C_{ih} = \overline{D_{ih}}$$

$$\overline{D_{iyl}} + \overline{d_{il}} = \overline{Y_{ifl}} + \overline{h_{il}}$$

(25)

and (8) - (10), (14), (15), (17) - (19), (22).

\(C_{i}^{\text{opt}}\) is denoted as the optimal solution of the cost function for the original problem and \(C_{i}^{\text{opt}}\) is denoted as the optimal solution of the cost function for the relaxed problem. Any feasible solution to original problem is also a feasible solution to the relaxed problem, i.e., the relaxed problem is less constrained.
than the original problem. Therefore, $C^\text{opt}_{ir} \leq C^\text{opt}_i$.

The optimal solution to the relaxed problem can be got by the stationary and randomized policy $\Pi$, stated as follows:

$$E\{C^\Pi(t)\} = C^\text{opt}_{ir}$$

subject to:

$$C^\Pi_{ic}(t) = D^\Pi_{ic}(t)$$
$$C^\Pi_{ig}(t) = D^\Pi_{ig}(t)$$
$$C^\Pi_{ih}(t) = D^\Pi_{ih}(t)$$
$$D^\Pi_{ig}(t) + d^\Pi_{il}(t) = Y^\Pi_{ifl}(t) + h^\Pi_{il}(t)$$

and (8) - (10), (14), (15), (17) - (19), (22).

The existence of the stationary and randomized policy can be proved by the Caratheodory theory [43]. Obviously, only if the solutions to the relaxed problem can meet the constraints (5) - (7) and (16), they are also feasible to the original problem. To reach this objective, the constants $\theta_i, \xi_i, \varepsilon_i$ and $\gamma_{il}$ are defined. These constants are adjusted appropriately to make the solutions to the relaxed problem also be feasible to the original problem. To start, the virtual queues $A_i(t), F_i(t), Z_i(t)$ and $I_{il}(t)$ for battery, hydrogen storage, water tank of microgrid $i$ and hydrogen storage of fuel cell vehicle $l_i$ are defined as follows, respectively:

$$A_i(t) = B_i(t) - \theta_i, F_i(t) = Y_i(t) - \xi_i$$
$$Z_i(t) = W_i(t) - \varepsilon_i, I_{il}(t) = Y_{il}(t) - \gamma_{il}$$

where $\theta_i, \xi_i$ and $\varepsilon_i$ and $\gamma_{il}$ are perturbations which are used to guarantee the bound of $B_i(t), Y_i(t), W_i(t)$ and $Y_{il}(t)$.

The Lyapunov function is defined as $Q_i(t) = \frac{1}{2}A_i(t)^2 + \frac{1}{2}F_i(t)^2 + \frac{1}{2}Z_i(t)^2 + \frac{1}{2}\sum_{l=1}^{L_i} I_{il}(t)^2$. The conditional Lyapunov drift which represents the change of
the Lyapunov function is defined as:

\[ \Delta_i(t) = \mathbb{E}\{Q_i(t + 1) - Q_i(t) | B_i(t), Y_i(t), W_i(t), Y_{il}(t)\} \]

where the expectation is related to the random processes of system, given the values \(B_i(t), Y_i(t), W_i(t), Y_{il}(t)\). According to the equation for the virtual queue \(28\) associated with the evolution of the battery, hydrogen storage and water tank in \(1\) - \(3\) and the hydrogen storage of fuel cell vehicle in \(13\), the Lyapunov drift is bounded as:

\[ \Delta_i(t) = \mathbb{E}\{Q_i(t + 1) - Q_i(t) | B_i(t), Y_i(t), W_i(t), Y_{il}(t)\} \]

\[ \leq G_i + \mathbb{E}\{A_i(t)(C_{ie}(t) - D_{ie}(t)) + F_i(t)(C_{iy}(t) - D_{iy}(t)) + Z_i(t)(C_{ih}(t) - D_{ih}(t)) + \sum_{l=1}^{L_i} [I_{il}(t)(D_{iyl}(t) + d_{il}(t) - Y_{il}(t) - h_{il}(t))]\} \]

\[ (30) \]

where \(G_i\) is constant and \(G_i = \frac{1}{2}\{\max(C_{ie,\text{max}}^2, D_{ie,\text{max}}^2) + \max(C_{iy,\text{max}}^2, D_{iy,\text{max}}^2) + \max(C_{ih,\text{max}}^2, D_{ih,\text{max}}^2) + \sum_{l=1}^{L_i} [\max((D_{iyl,\text{max}} + d_{il,\text{max}})^2, (Y_{il,\text{max}} + h_{il,\text{max}})^2)]\}\). The proof of this step is in Appendix A.

In order to make these queues stable, microgrid \(i\) needs to minimize the drift \(\Delta_i(t)\). In addition, microgrid \(i\) intends to minimize the energy cost. Hence, \(V_i\) is used to represent the tradeoff between the two objectives. Then the drift-
plus-penalty function is denoted as:

\[ \Delta_i(t) + V_i \mathbb{E}\{C_i(t)\} \leq G_i + \mathbb{E}\{A_i(t)(C_{ie}(t) - D_{ie}(t)) + F_i(t)(C_{iy}(t) - D_{iy}(t)) + Z_i(t)(C_{ih}(t) - D_{ih}(t)) + \sum_{l=1}^{L_i} |I_{il}(t)(D_{isl}(t) + d_{il}(t) - Y_{i,fi}(t) - h_{il}(t))|} + V_i \mathbb{E}\{C_i(t)\} \]

\[ = G_i + \mathbb{E}\{A_i(t)(C_{ie}(t) - D_{ie}(t)) + F_i(t)(C_{iy}(t) - D_{iy}(t)) + Z_i(t)(C_{ih}(t) - D_{ih}(t)) + \sum_{l=1}^{L_i} |I_{il}(t)(D_{isl}(t) + d_{il}(t) - Y_{i,fi}(t) - h_{il}(t))| + V_i(p_y(t)d_i(t) + E_i(t)p_e(t)) + (P_{1,CHP}(t) + H_{1,CHP}(t) + H_{1,p}(t))p_g(t) + \beta_i(t)X_i(t) - \alpha_i(t)S_i(t) - E_{i,o}(t)p_{co}(t)\}\]

\[ (31) \]

The relaxed problem can be viewed as minimizing the cost of microgrid while maintaining the stability of virtual queues. The drift-plus-penalty term consists of two terms, the Lyapunov drift term \( \Delta_i(t) \), and modified cost term \( V_i \mathbb{E}\{C_i(t)\} \). Larger value of \( V_i \) means that minimizing the energy cost has greater priority than minimizing the drift, and vice versa. The objective of Lyapunov optimization is to minimize the right hand of (31), i.e.

\[ \min_{M_i(t)} A_i(t)(C_{ie}(t) - D_{ie}(t)) + F_i(t)(C_{iy}(t) - D_{iy}(t)) + Z_i(t)(C_{ih}(t) - D_{ih}(t)) + \sum_{l=1}^{L_i} |I_{il}(t)(D_{isl}(t) + d_{il}(t) - Y_{i,fi}(t) - h_{il}(t))| + V_i(p_y(t)d_i(t) + E_i(t)p_e(t)) + (P_{1,CHP}(t) + H_{1,CHP}(t) + H_{1,p}(t))p_g(t) + \beta_i(t)X_i(t) - \alpha_i(t)S_i(t) - E_{i,o}(t)p_{co}(t)\]

\[ (32) \]

subject to the constraints [8] - [10], [14], [15], [17] - [19], [22].

In the following section, the price and amount of energy in energy trading among microgrids are determined, and the optimal strategy of problem (32) is
obtained by solving the linear programming problem.

4.2. Double Auction

Optimization problem (32) has two variables of price. Owing to the decentralized structure of the energy trading, the selling price and purchase price can be determined by the external auctioneer according to the mechanism of double auction. Firstly the selling price and purchase price of each microgrid submitted in energy trading among microgrids are investigated.

**Lemma 1.** Microgrid $i$ decides the selling price $\tilde{\alpha}_i(t)$ or purchase price $\tilde{\beta}_i(t)$ based on the cost-minimization problem:

$$\tilde{\alpha}_i(t) = \max\left[-\frac{A_i(t)}{V_i}, \frac{-F_i(t)}{(\eta_e + c_1) V_i}, p_{eo}(t)\right]$$  \hspace{1cm} (33)

$$\tilde{\beta}_i(t) = \min\left[\max\left(-\frac{A_i(t)}{V_i}, 0\right), \frac{p_g}{\eta_{pg}}, p_e(t)\right]$$  \hspace{1cm} (34)

where $p_{eo}(t)$ is the price of energy sold to the electricity utility company by microgrid, and $p_{eo}(t) < p_e(t)$.

The proof of this step is in Appendix B.

After determining $\tilde{\alpha}_i(t)$ and $\tilde{\beta}_i(t)$, the amount of electricity $\tilde{S}_i(t)$ and $\tilde{X}_i(t)$ that microgrid $i$ will sell and purchase in energy trading are determined by solving (32). Microgrids are willing to sell their energy when their energy storages have enough energy. Moreover, they are willing to get energy when the cost of purchasing energy is lower than that of generating energy by themselves (such as generating electricity by CHP and using hydrogen). The maximum amount of electricity that microgrid $i$ can sell $S_{i,max}(t)$ and purchase $X_{i,max}(t)$ at time slot $t$ are:

$$S_{i,max}(t) = N_i(t) - L_{ie}(t)$$  \hspace{1cm} (35)

$$X_{i,max}(t) = L_{ie}(t) - N_i(t)$$  \hspace{1cm} (36)

A mechanism of double auction is designed to encourage microgrids to trade energy actively and ensure the benefits of microgrids. The mechanism of double
auction has two steps:

- Microgrids submit the selling price, purchase price and the corresponding amount of energy to external auctioneer.
- External auctioneer decides the accepted selling price and purchase price by trading rules, and allocates energy to microgrids to minimize the transmission loss.

The mechanism of Threshold Price Double Auction [44] is shown in this section. Firstly, the external auctioneer collects and sorts all received purchase prices in descending order and selling prices in ascending order: \( \beta_1(t) \geq \beta_2(t) \geq \cdots \geq \beta_i(t) \geq r > \beta_{i+1}(t) \geq \cdots \geq \beta_n(t) \) and \( \alpha_1(t) \leq \alpha_2(t) \leq \cdots \leq \alpha_j(t) \leq r < \alpha_{j+1}(t) \leq \cdots \leq \alpha_n(t) \). If \( i = j \), the external auctioneer notifies microgrids, \( l = 1,2,\cdots,i \), that they can trade. The accepted selling price and purchase price are \( \alpha(t) = \beta(t) = r \). If \( i > j \), the external auctioneer notifies microgrids, \( l = 1,2,\cdots,j \), that they can trade. The accepted selling price and purchase price are \( \alpha(t) = r \) and \( \beta(t) = \beta_{j+1}(t) \). If \( i < j \), the external auctioneer notifies microgrids, \( l = 1,2,\cdots,i \), that they can trade. The accepted selling price and purchase price are \( \alpha(t) = \alpha_{i+1}(t) \) and \( \beta(t) = r \).

The accepted purchase price and selling price for microgrid \( i \) can be derived as:

\[
\hat{\beta}_i(t) = \begin{cases} 
\beta(t) & \text{if microgrid } i \text{ purchases electricity} \\
0 & \text{otherwise}
\end{cases}
\]

and

\[
\hat{\alpha}_i(t) = \begin{cases} 
\alpha(t) & \text{if microgrid } i \text{ sells electricity} \\
0 & \text{otherwise}
\end{cases}
\]

After determining the market clearance prices, the external auctioneer needs to match energy sellers and buyers to reduce energy losses.

\[
Loss(t) = \sum_{i=1}^{k} \sum_{j=1}^{k} J_{ij} T_{ij}(t)
\]

where \( T_{ij}(t) \) is the amount of energy transmitted from microgrid \( i \) to microgrid
at time \( t \). \( I_{ij} \) is energy loss coefficient which is related to the transmission distance.

External auctioneer aims to minimize the energy losses during transmission:

\[
\min_{T_{ij}, \forall i,j \in [1,k]} \text{Loss}(t) \tag{40}
\]

subject to:

\[
\sum_{j=1}^{k} T_{ij} \leq S_i(t) \tag{41}
\]

\[
\sum_{i=1}^{k} (1 - I_{ij}) T_{ij} \geq X_j(t) \tag{42}
\]

After determining \( \alpha_i(t) \) and \( \beta_i(t) \), the actual amount of electricity that microgrid \( i \) sells \( S_i^*(t) \) or purchases \( X_i^*(t) \) can be determined to minimize the energy losses during transmission by linear programming. The performance of the proposed trading mechanism is as follows.

**Lemma 2.** Using the mechanism presented above, all microgrids will submit the selling prices and purchase prices truthfully, otherwise they will get lower benefits owing to deviating from the true value of the selling prices and purchase prices in (33) and (34).

The proof of this step is in Appendix C.

### 4.3. Algorithm Design and Performance Analysis

After obtaining \( X_i^*(t) \) and \( S_i^*(t) \) by (40)-(42) and double auction, an optimal strategy set of microgrid \( i \) can be acquired by solving the linear programming problem (32): \( M_i^*(t) = \{ C_{ie}^*(t), D_{ie}^*(t), C_{iy}^*(t), D_{iy}^*(t), C_{ih}^*(t), D_{ih}^*(t), D_{iyh}^*(t), d_{il}^*(t), Y_{ij}^*(t), h_{il}^*(t), E_i^*(t), P_i^{CHP*}(t), H_i^{CHP*}(t), H_i^{b*}(t), X_i^*(t), S_i^*(t), E_i^{io}(t) \} \) to minimize the drift-plus-penalty. The implementation process of algorithm is shown in Algorithm 1.

In the aforementioned design, the capacity constraints of the battery, hydrogen storage and water tank of microgrid \( i \) and hydrogen storage of fuel cell vehicle \( l_i \) are not considered. Thus, the capacity constraints are analyzed as
Algorithm 1 Joint Energy Scheduling and Trading Algorithm

1: Set $t = 0$.
2: Set the initial value $B_i(t), Y_i(t), W_i(t)$ and $Y_{il}(t)$.
3: for each microgrid $i$ do
4:  Calculate $\alpha_i(t)$ and $\beta_i(t)$ by (33) and (34), calculate $X_i(t)$ and $S_i(t)$ by (32), then submit them to external auctioneer.
5:  Calculate $\alpha_i(t), \beta_i(t), X_i(t)$ and $S_i(t)$ by double auction.
6:  Calculate $M_i(t)$ by (32).
7: Update $B_i(t + 1), Y_i(t + 1), W_i(t + 1)$ by (1) - (3) and $Y_{il}(t + 1)$ by (13).

Lemma 3. If $\theta_i, \xi_i, \varepsilon_i, \gamma_{il}$ and $V_i$ satisfy following conditions:

$$\theta_i = V_ip_{e,max} + D_{ie,max}$$ (43)
$$\xi_i = V_ip_{y,max} + D_{iy,max}$$ (44)
$$\varepsilon_i = V_ip_{g,max} + D_{ih,max}$$ (45)
$$\gamma_{il} = V_ip_{y,max} + Y_{ifl,\max} + h_{il,\max}$$ (46)
$$V_{i,max} = \min\{\frac{B_{i,max} - C_{ie,max} - D_{ie,max}}{p_{e,max}}, \frac{Y_{i,max} - C_{iy,max} - D_{iy,max}}{p_{y,max}}, \frac{\eta_{bg} (W_{i,max} - C_{ih,max} - D_{ih,max})}{p_{g,max}}, \frac{Y_{il,max} - D_{ipl,max} - d_{il,max} - Y_{ifl,\max} - h_{il,\max}}{p_{y,max}}\}$$ (47)

where $0 \leq V_i \leq V_{i,max}$, the capacity constraints of the battery, hydrogen storage and water tank of microgrid $i$ and hydrogen storage of fuel cell vehicle $l_i$ are always satisfied.

The proof of this step is in Appendix D.

According to Lemma 3, the algorithm satisfies the capacity constraints of the battery, hydrogen storage and water tank of microgrid $i$ and hydrogen storage of fuel cell vehicle $l_i$ in the original problem, i.e. constraints (5) - (7) and (16).

Hence, the algorithm is feasible for the original problem. The choice of the
perturbation parameter $\theta_i$, $\epsilon_i$, $\xi_i$ and $\gamma_{il}$ is reasonable. Then the result about the performance of algorithm based on Lyapunov optimization is provided.

**Theorem 1.** According to the algorithm in the previous section, the expected time average energy cost has a bound:

$$
\lim_{T \to \infty} \frac{1}{T} \sum_{t=1}^{T} E\{C_i(t)\} \leq C_i^{opt} + \frac{G_i}{V_i}
$$

(48)

The proof of this step is in Appendix E. In a sense, Theorem 1 shows how gap between the performance of proposed algorithm independent of random distribution factors and optimization algorithm with accurate random information is described. According to (47) and Theorem 1, as the battery, hydrogen storage and water tank capacity of microgrid $i$ and hydrogen storage capacity of fuel cell vehicle $l_i$ increase, the performance of proposed algorithm can be made arbitrarily close to the optimal performance of optimization algorithm with accurate random information.

5. Numerical Results

In this section, the numerical results based on real data are presented to examine the proposed algorithm in the previous sections.

5.1. Experimental Setup

A network of three microgrids is considered. Each microgrid includes renewable energy resource, CHP, fuel cell vehicles, battery, hydrogen storage, boiler and water tank. Wind-driven turbines and photovoltaic systems are the renewable energy generators whose maximum outputs are 750 kW for microgrid 1 and 2, and 450 kW for microgrid 3. For each microgrid’s electricity loads, the hourly load data provided by pjm hourly load [45] is shown in Fig. 2(a). For the renewable energy generation, the hourly generation data provided by Renewables.ninja [46] is shown in Fig. 2(b). For the price of the electricity utility company, the hourly energy price provided by the Power Smart Pricing administered for Ameren Illinois data [47] is shown in Fig. 2(c).
The maximum electricity consumption of electrolysis system is 100 kW. The total amount of hydrogen consumed by each microgrid’s all vehicles which are used for driving takes value from [25, 35] m$^3$ at random during a time slot. When the hydrogen in hydrogen storage of microgrid cannot supply the vehicles, the vehicles will purchase hydrogen from hydrogen station of the hydrogen-producing company. In this paper, the fuel cell vehicles refer to buses. Each microgrid has 10 fuel cell buses. The hydrogen that each bus consumes is about 0.5 m$^3$/km, and the maximum generation of the bus is 45 kW. The buses will depart every 20 minutes from 6:00 a.m to 10:00 p.m. At 6:00 a.m., there are 5 buses at the starting point and the bus terminal of each microgrid, respectively. The distance from the starting point to the bus terminal is about 10 km and it takes 40-60 minutes to do the journey.

The heat and electricity generation of CHP satisfies $H_{CHP}^i(t) = P_{CHP}^i(t)$. The parameters of efficiency are $\eta_{pg} = 70\%$, $\eta_{hg} = 70\%$, $\eta_{bg} = 80\%$, $\eta_e = 85\%$ and $\eta_f = 50\%$ respectively. Other parameters are summarized as follows:

- $p_g(t) = 10$ cents/m$^3$, $p_h(t) = 15$ cents/m$^3$, $B_{i, max} = 300$ kWh, $C_{ie, max} = D_{ie, max} = 75$ kWh, $W_{i, max} = 900$ kWh, $C_{ih, max} = D_{ih, max} = 225$ kWh, $Y_{i, max} = 300$ m$^3$, $C_{iy, max} = D_{iy, max} = 75$ m$^3$.

5.2. Results

The fuel cell vehicles and hydrogen storages play important roles in relieving storage stress of battery and further using excess renewable energy. Fig. 3 shows that the costs of microgrids are lower than those without hydrogen storage. The
existence of hydrogen storage obviously reduces the costs of microgrids 1 and 2. The cost of microgrid 3, however, slightly reduces. The reason is that microgrids 1 and 2 electrolyze water to supply hydrogen for the fuel cell vehicles instead of selling electricity to the electricity company at a low price. Therefore, the costs of microgrids 1 and 2 obviously reduce. Since the renewable energy of microgrid 3 is not enough, microgrid 3 needs to purchase energy. In Fig. 6(c), microgrid 3 with hydrogen storage electrolyzes water to supply a little hydrogen for the fuel cell vehicles and microgrid 3 without hydrogen storage charges the battery. Both of them purchase much hydrogen from hydrogen-producing company. Therefore, the cost of microgrid 3 with hydrogen slightly reduces in Fig. 3.

Then, the comparisons of the costs, energy trading and battery dynamics with and without hydrogen storage for all three microgrids across 24 time slots are presented in Figs. 4-6. In the energy trading, the positive values denote purchasing energy, and the negative values denote selling energy. Fig. 4 denotes that microgrids achieve lower costs with hydrogen storage in most cases, where microgrids electrolyze water to supply hydrogen for fuel cell vehicles or store hydrogen for the demand in future instead of selling electricity to the electricity utility company at a low price. Fig. 5 denotes the comparison of energy trading dynamics with and without hydrogen storage. Microgrid 1 sells more electricity to other microgrids with hydrogen storage. This is because microgrid 3 needs more electricity to electrolyze water to generate hydrogen for fuel cell vehicles, so microgrid 3 purchases more electricity from microgrid 1. Fig. 6 denotes the comparison of battery dynamics with and without hydrogen storage. All microgrids charge less electricity into battery with hydrogen storage. This is because microgrids with hydrogen storage use some electricity to electrolyze water to generate hydrogen.

Energy trading plays an important role in releasing the unbalance of supply and demand for single microgrid. Fig. 7 shows the costs of microgrids are lower than those without trading. Energy trading obviously reduces the cost of microgrid 1. The costs of microgrids 2 and 3, however, slightly reduce. The reason is that the renewable energy of microgrid 1 is more than the demand in
Fig. 3. Comparisons of all microgrids’ total costs with and without hydrogen storage

(a) Microgrid 1  (b) Microgrid 2  (c) Microgrid 3

Fig. 4. Costs of each microgrid with and without hydrogen storage

(a) Microgrid 1  (b) Microgrid 2  (c) Microgrid 3

Fig. 5. Energy trading of each microgrid with and without hydrogen storage.

(a) Microgrid 1  (b) Microgrid 2  (c) Microgrid 3

Fig. 6. Battery dynamics of each microgrid with and without hydrogen storage.
most cases. Microgrid 1 sells electricity to microgrid 2 and 3 instead of selling electricity to the electricity company at a low price in most cases. Therefore, the cost of microgrid 1 obviously reduces. Microgrid 3 without energy trading cannot purchase electricity from microgrid 1 at a low price, but it can generate electricity by CHP at a cost which is lower than the cost of purchasing electricity from the electricity company, and microgrid 2 trades a little energy with other microgrids. Therefore, the costs of microgrids 2 and 3 with trading slightly reduce in Fig. 7.

Then, the comparisons of the costs, battery and hydrogen storage dynamics with and without energy trading for all three microgrids across 24 time slots are presented in Figs. 8-10. Fig. 8 denotes that microgrids achieve lower costs with energy trading in most cases, where microgrids acquire electricity from other microgrids in energy trading instead of the electricity utility company. Fig. 2(b) tells that microgrid 1 have higher renewable energy output than other microgrids, so microgrid 1 sell excessive energy to other microgrids in most cases except the last four hours. The reason is that microgrid 1 has a drop of renewable energy output at the last four hours, while microgrid 2 has adequate renewable energy output at the last four hours. Fig. 9 denotes the comparison of battery dynamics with and without energy trading. Microgrid 1 charges less electricity into battery with energy trading. This is because microgrid 1 sells electricity to other microgrids instead of storing electricity in battery. It’s the same as hydrogen storage in Fig. 10. Whether it involves trading or not, microgrid 3 without abundant renewable energy to electrolyze water, has to purchase hydrogen from hydrogen-producing company to supply vehicles. Therefore, microgrid 3 has not energy to charge and the dynamics of storage level of microgrid 3 is the same as in Fig. 9 and Fig. 10.

Table 1 shows the costs of three microgrids of the proposed method, without hydrogen storage and without energy trading. Three cases of different initial energy storages are studied as follows. 1) The initial energy of storage is 10% of its capacity (Figs. 3-10 are generated in this case). The total cost of three microgrids is reduced by up to 26.53% from 28563 cents without hydrogen storage.
Fig. 7. Comparisons of all microgrids’ total costs with and without energy trading.

Fig. 8. Costs of each microgrid with and without energy trading.

Fig. 9. Battery dynamics of each microgrid with and without energy trading.

Fig. 10. Hydrogen storage dynamics of each microgrid with and without energy trading.
Table 1: Cost(cent)

| initial energy storage | Microgrid | 1  | 2  | 3  | total |
|------------------------|-----------|----|----|----|-------|
| 10% of capacity        | Cost      | 3091| 3887| 14006| 20984 |
|                        | Cost(without trading) | 3419| 4319| 14425| 24163 |
|                        | Cost(without hydrogen) | 7327| 7005| 14231| 28563 |
| 50% of capacity        | Cost      | 2060| 3377| 12931| 18367 |
|                        | Cost(without trading) | 3570| 3758| 13536| 21844 |
|                        | Cost(without hydrogen) | 6392| 6491| 13239| 26121 |
| 100% of capacity       | Cost      | 807 | 2198| 11758| 14763 |
|                        | Cost(without trading) | 3419| 2567| 12364| 18350 |
|                        | Cost(without hydrogen) | 5509| 5317| 12061| 22888 |

to 20984 cents, and 13.16% from 24163 cents without energy trading to 20984 cents. 2) The initial energy of storage is 50% of its capacity. The total cost of three microgrids is reduced by up to 29.68% from 26121 cents without hydrogen storage to 18367 cents, and 15.92% from 21844 cents without energy trading to 18367 cents. 3) The initial energy of storage is its capacity. The total cost of three microgrids is reduced by up to 35.5% from 22888 cents without hydrogen storage to 14763 cents, and 19.55% from 18350 cents without energy trading to 14763 cents. According to the simulations, the cost decreases with an increase in the initial energy of storage, and the extent of cost reduction increases with an increase in the initial energy of storage. This is because more initial energy of storage means less cost of purchasing energy and more energy used to trade or electrolyze water. The introduction of hydrogen storage and energy trading reduces the costs of all microgrids. Therefore, microgrids benefit with energy trading, hydrogen storage and fuel cell vehicles. This denotes the effectiveness of the proposed algorithm.

6. Conclusion

In this paper, the problem of energy scheduling and energy trading for real-time pricing among microgrids is studied, which is the imperative issue faced by the cyber-physical-energy system. A multi-energy management framework including fuel cell vehicles, energy storage, CHP and renewable energy is pre-
sented, where fuel cell vehicles and energy storage further realize the absorption of renewable energy. A joint algorithm based on Lyapunov optimization and double auction is designed to solve the energy scheduling and trading problem of microgrids to meet energy demands. Meanwhile, this algorithm can ensure economic benefit and truthfulness, and realize the time average cost minimization. Such an energy scheduling and trading mechanism can promote the active participation of both sellers and buyers. At last, the results based on real data show that microgrids’ costs can be decreased by the proposed algorithm. Comparative analyses on energy storage and energy trading demonstrate the necessity of equipping energy storage and trading energy.

In this paper, the fuel cell vehicles refer to buses which have specific route. Due to transportation concern, a more realistic scenario is that the fuel cell vehicles can be cars, buses and so on. In this case, the trip characteristics of vehicles need to be considered. Investigating some control schemes, e.g., Ref. [48], to optimize dispatch of the fuel cell vehicles is a significant research direction. Another direction is how to design scheduling method, e.g., Ref. [49], to further realize the multi-energy coupled peak load shifting in realistic scenario, such as industrial parks.
Appendix A. Proof of (30)

According to (1)-(3), (13) and (28), the Lyapunov drift term \( \Delta_i(t) \) is denoted by

\[
\Delta_i(t) = \mathbb{E}\{Q_i(t + 1) - Q_i(t) | B_i(t), Y_i(t), W_i(t), Y_{il}(t)\} \\
= \frac{1}{2} \mathbb{E}\{2A_i(t)(C_{ie}(t) - D_{ie}(t)) + 2F_i(t)(C_{iy}(t) - D_{iy}(t)) \\
+ 2Z_i(t)(C_{ih}(t) - D_{ih}(t)) + \sum_{l=1}^{L_i}[2I_{il}(t)(D_{iyl}(t) + d_{il}(t) \\
- Y_{iff}(t) - h_{il}(t))] + (C_{ie}(t) - D_{ie}(t))^2 \\
+ (C_{iy}(t) - D_{iy}(t))^2 + (C_{ih}(t) - D_{ih}(t))^2 \\
+ \sum_{l=1}^{L_i}[D_{iyl}(t) + d_{il}(t) - Y_{iff}(t) - h_{il}(t)]^2\} \\
\leq \frac{1}{2} \mathbb{E}\{2A_i(t)(C_{ie}(t) - D_{ie}(t)) + 2F_i(t)(C_{iy}(t) - D_{iy}(t)) \\
+ 2Z_i(t)(C_{ih}(t) - D_{ih}(t)) + \sum_{l=1}^{L_i}[2I_{il}(t)(D_{iyl}(t) + d_{il}(t) \\
- Y_{iff}(t) - h_{il}(t))] + \max(C_{ie,\text{max}}^2, D_{ie,\text{max}}^2) \\
+ \max(C_{iy,\text{max}}^2, D_{iy,\text{max}}^2) + \max(C_{ih,\text{max}}^2, D_{ih,\text{max}}^2) \\
+ \sum_{l=1}^{L_i}[\max((D_{iyl,\text{max}} + d_{il,\text{max}})^2, (Y_{iff,\text{max}} + h_{il,\text{max}}^2))]\} \\
= \mathbb{E}\{A_i(t)(C_{ie}(t) - D_{ie}(t)) + F_i(t)(C_{iy}(t) - D_{iy}(t)) \\
+ Z_i(t)(C_{ih}(t) - D_{ih}(t)) + \sum_{l=1}^{L_i}[I_{il}(t)(D_{iyl}(t) + d_{il}(t) \\
- Y_{iff}(t) - h_{il}(t))] + G_i \}
\]

where \( G_i = \frac{1}{2}(\max(C_{ie,\text{max}}^2, D_{ie,\text{max}}^2) + \max(C_{iy,\text{max}}^2, D_{iy,\text{max}}^2) + \max(C_{ih,\text{max}}^2, D_{ih,\text{max}}^2) + \sum_{l=1}^{L_i}\max((D_{iyl,\text{max}} + d_{il,\text{max}})^2, (Y_{iff,\text{max}} + h_{il,\text{max}}^2))]\} \)
Appendix B. Proof of Lemma 1

The following four cases are considered to determine the price of energy trading.

1. Case 1: $A_i(t) \geq 0$. In this case, microgrid $i$ has too much energy in its battery. According to (22), $C_{ie}(t) - D_{ie}(t) = E_{i}(t) + N_i(t) + X_i(t) - S_i(t) + \eta_f hY_{if}(t) - \frac{hC_{iy}(t)}{\eta_e} - c_1C_{iy}(t) + \eta_{pg}F_i^{CHP}(t) - E_{io}(t) - L_{ie}(t)$. According to (32), i.e.

$$
\begin{align*}
\min_{M_i(t)} A_i(t)(C_{ie}(t) - D_{ie}(t)) + F_i(t)(C_{iy}(t) - D_{iy}(t)) \\
+ Z_i(t)(C_{ih}(t) - D_{ih}(t)) + \sum_{l=1}^{L_i} [I_{il}(t)(D_{iyl}(t) + d_{il}(t)] \\
- Y_{ifl}(t) - h_{il}(t)]) + V_i(p_{g}(d_i(t)) + E_i(t)p_e(t) \\
+ (P_i^{CHP}(t) + H_i^{CHP}(t) + H_i^{X}(t)p_g(t) + \beta_i(t)X_i(t) \\
- \alpha_i(t)S_i(t) - E_{io}(t)p_{eo}(t)) \\
= \min_{M_i(t)} -(A_i(t) + V_i\alpha_i(t))S_i(t) + (A_i(t) + V_i\beta_i(t))X_i(t) \\
+ A_i(t)(E_{i}(t) + N_i(t) + \frac{hC_{iy}(t)}{\eta_e} - \frac{hC_{iy}(t)}{\eta_e} \\
- c_1C_{iy}(t) + \eta_{pg}F_i^{CHP}(t) - E_{io}(t) - L_{ie}(t)) \\
+ F_i(t)(C_{iy}(t) - D_{iy}(t)) + Z_i(t)(C_{ih}(t) - D_{ih}(t)) \\
+ \sum_{l=1}^{L_i} [I_{il}(t)(D_{iyl}(t) + d_{il}(t) - Y_{ifl}(t) - h_{il}(t)]) \\
+ V_i(p_g(t)d_i(t) + E_i(t)p_e(t) + (P_i^{CHP}(t) + H_i^{CHP}(t) \\
+ H_i^{X}(t))p_g(t) - E_{io}(t)p_{eo}(t))
\end{align*}
$$

(B.1)

and $-\alpha_i(t)V_i - A_i(t) < 0$, microgrid $i$ tends to increase $S_i(t)$, and $C_{ie}(t) = 0$, $D_{ie}(t) = D_{ie,\max}$.

2. Case 2: $A_i(t) < 0$. In this case, six situations are considered.

- If $0 < \alpha_i(t) < -\frac{A_i(t)}{V_i}$, then $-\alpha_i(t)V_i - A_i(t) > 0$. Therefore, microgrid $i$ tends to decrease $S_i(t)$ and increase $C_{ie}(t)$.
• If $\alpha_i(t) > -\frac{A_i(t)}{V_i}$, then $-A_i(t) - \alpha_i(t)V_i < 0$. Therefore, microgrid $i$ tends to increase $S_i(t)$ and decrease $C_{i\epsilon}(t)$.

• If $\alpha_i(t) = -\frac{A_i(t)}{V_i}$, then $-A_i(t) - \alpha_i(t)V_i = 0$. It is same for microgrid $i$ to increase $S_i(t)$ or increase $C_{i\epsilon}(t)$.

• If $0 < \beta_i(t) < -\frac{A_i(t)}{V_i}$, then $\beta_i(t)V_i + A_i(t) < 0$. Therefore, microgrid $i$ tends to increase $X_i(t)$ and decrease $D_{i\epsilon}(t)$.

• If $\beta_i(t) > -\frac{A_i(t)}{V_i}$, then $A_i(t) + \beta_i(t)V_i > 0$. Therefore, microgrid $i$ tends to decrease $X_i(t)$ and increase $D_{i\epsilon}(t)$.

• If $\beta_i(t) = -\frac{A_i(t)}{V_i}$, then $-A_i(t) = \beta_i(t)V_i$. It is same for microgrid $i$ to increase $X_i(t)$ or increase $D_{i\epsilon}(t)$.

3. Case 3: $F_i(t) \geq 0$. In this case, microgrid $i$ has too much hydrogen in its hydrogen storage. According to (22),

$$
\left(\frac{h}{\eta_e} + c_1\right)C_{iy}(t) = E_i(t) + N_i(t) + X_i(t) - S_i(t) - C_{i\epsilon}(t) + D_{i\epsilon}(t) + \eta_f h Y_{ij}(t) + \eta_{pg} P_{CHP_i}(t) - E_{i\epsilon}(t) - L_{i\epsilon}(t).
$$
According to [32], i.e.

\[
\begin{align*}
\min_{M_i(t)} & \ A_i(t)(C_{ie}(t) - D_{ie}(t)) + F_i(t)(C_{iy}(t) - D_{iy}(t)) \\
& + Z_i(t)(C_{ih}(t) - D_{ih}(t)) + \sum_{i=1}^{L_i} [I_{il}(t)D_{ily}(t) + d_{il}(t)] \\
& - Y_{if}(t) - h_{il}(t)) + V_i(p_y(t)d_i(t) + E_i(t)p_e(t) \\
& + (P_i^{CHP}(t) + H_i^{CHP}(t) + H_i^h(t))p_y(t) + \beta_i(t)X_i(t) \\
& - \alpha_i(t)S_i(t) - E_{io}(t)p_{eo}(t)) \\
= \min_{M_i(t)} & \ A_i(t)(C_{ie}(t) - D_{ie}(t)) - (\frac{F_i(t)}{\eta_i} + V_i\alpha_i(t))S_i(t) \\
& + (\frac{F_i(t)}{\eta_i} + V_i\beta_i(t))X_i(t) + \frac{F_i(t)}{\eta_i}(E_i(t) + N_i(t) \\
& - C_{ie}(t) + D_{ie}(t) + \eta_f Y_{if}(t) + \eta_{pg} P_i^{CHP}(t) - E_{io}(t) \\
& - L_{ie}(t) - F_i(t)D_{iy}(t) + Z_i(t)(C_{ih}(t) - D_{ih}(t)) \\
& + \sum_{i=1}^{L_i} [I_{il}(t)D_{ily}(t) + d_{il}(t) - Y_{if}(t) - h_{il}(t)) \\
& + V_i(p_y(t)d_i(t) + E_i(t)p_e(t) - E_{io}(t)p_{eo}(t) \\
& + (P_i^{CHP}(t) + H_i^{CHP}(t) + H_i^h(t))p_y(t)) \\
\end{align*}
\]

and \(-\alpha_i(t)V_i - \frac{F_i(t)}{\eta_i} < 0\), microgrid \(i\) tends to increase \(S_i(t)\), and \(C_{iy}(t) = 0, D_{iy}(t) = D_{iy,max}\).

4. Case 4: \(F_i(t) < 0\). In this case, three situations are considered.

- If \(0 < \alpha_i(t) < \frac{-F_i(t)}{(\frac{F_i}{\eta_i} + \gamma_i)V_i}\), then \(-\alpha_i(t)V_i - \frac{F_i(t)}{\eta_i} < 0\). Therefore, microgrid \(i\) tends to decrease \(S_i(t)\) and increase \(C_{iy}(t)\).

- If \(\alpha_i(t) > \frac{-F_i(t)}{(\frac{F_i}{\eta_i} + \gamma_i)V_i}\), then \(-\alpha_i(t)V_i - \frac{F_i(t)}{\eta_i} < 0\). Therefore, microgrid \(i\) tends to increase \(S_i(t)\) and decrease \(C_{iy}(t)\).

- If \(\alpha_i(t) = \frac{-F_i(t)}{(\frac{F_i}{\eta_i} + \gamma_i)V_i}\), then \(-\alpha_i(t)V_i - \frac{F_i(t)}{\eta_i} = 0\). It is same for microgrid \(i\) to increase \(S_i(t)\) or increase \(C_{iy}(t)\).
Appendix C. Proof of Lemma 2

All microgrids are rational. They will choose a strategy which can minimize their costs. The purchase price and selling price submitted by microgrid $i$ are $\beta_i(t)$ and $\alpha_i(t)$, and the purchase price and selling price determined by the double auction are $\hat{\beta}(t)$ and $\hat{\alpha}(t)$ in the actual energy trading. Then the benefit of microgrid $i$ is analyzed when it cheats.

1. Case 1: $\alpha_i(t) > \hat{\alpha}(t)$. In this case, microgrid $i$ is not allowed to sell energy in double auction.
   - If microgrid increases $\alpha_i(t)$, the situation does not change.
   - If microgrid reduces $\alpha_i(t)$ and $\alpha_i(t) > \hat{\alpha}(t)$, the situation does not change.
   - If microgrid reduces $\alpha_i(t)$ and $\alpha_i(t) \leq \hat{\alpha}(t)$, the microgrid will be forced to sell energy with the price lower than expected, and its benefit will decrease owing to cheating.

2. Case 2: $\alpha_i(t) \leq \hat{\alpha}(t)$. In this case, microgrid sells energy in double auction.
   - If microgrid reduces $\alpha_i(t)$, the situation does not change.
   - If microgrid increases $\alpha_i(t)$ and $\alpha_i(t) \leq \hat{\alpha}(t)$, the situation does not change.
   - If microgrid increases $\alpha_i(t)$ and $\alpha_i(t) > \hat{\alpha}(t)$, the microgrid is not allowed to sell energy in double auction. However, energy is excessive, microgrid may sell excessive energy to the electricity utility company with lower price, and its benefit will decrease owing to cheating.

It is similar to analyze $\beta_i(t)$. Therefore, the double auction can prevent microgrids cheating.

Appendix D. Proof of Lemma 3

The induction is used to prove the bound of $B_i(t)$, $Y_i(t)$, $W_i(t)$ and $Y_{ii}(t)$. First the conditions hold at time slot 1 and still hold at time slot $t$. Then the following four cases are considered as follows.
1. Case 1: $B_i(t) < \theta_i$. In this case, $C_{ie}(t) \leq C_{ie,\max}$, and $\theta_i = V_i p_{e,\max} + D_{ie,\max} \leq B_{i,\max} - C_{ie,\max}$. Therefore, $B_i(t + 1) \leq B_i(t) + C_{ie,\max} < \theta_i + C_{ie,\max} \leq B_{i,\max}$.

2. Case 2: $B_i(t) \geq \theta_i$. In this case, $C_{ie}(t) = 0$. The battery will not be charged at time slot $t$. Therefore, $B_i(t + 1) \leq B_i(t) \leq B_{i,\max}$.

3. Case 3: $B_i(t) < D_{ie,\max}$. In this case, $A_i(t) < D_{ie,\max} - \theta_i = -V_i p_{e,\max}$, then $A_i(t) + V_i \beta_i(t) < A_i(t) + V_i p_{e,\max} < 0$. According to (22) and (B.1), $D_{ie}(t) = 0$. Therefore, $B_i(t + 1) \geq B_i(t) \geq 0$.

4. Case 4: $B_i(t) \geq D_{ie,\max}$. In this case, $B_i(t + 1) = B_i(t) + C_{ie}(t) - D_{ie}(t) \geq B_i(t) - D_{ie}(t) \geq 0$.

It is similar to analyze the bound of $Y_i(t)$, $W_i(t)$ and $Y_{il}(t)$.

**Appendix E. Proof of Theorem 1**

The optimal solution of problem (32) is obtained to minimize the drift-plus-penalty. Comparing this optimal solution with the result of stationary random policy($\Pi$), the drift-plus-penalty term satisfies
\[ \Delta_i(t) + V_i \mathbb{E}\{C_i(t)\} \leq G_i + \mathbb{E}\{A_i(t)(C_i^*(t) - D^*_i(t)) + F_i(t)(C_{iy}^*(t) - D_{iy}^*(t)) \] 
\[ + Z_i(t)(C_i^*(t) - D^*_i(t)) + \sum_{l=1}^{L_i} [I_{il}(t)(D_{iy}^*(t) + d_{iy}^*(t)) \] 
\[ - Y^*_i(t) - D^*_i(t)] + V_i(p_y(t)d^*_i(t) + E^*_i(t)p_e(t) \] 
\[ + (P_i^{CHP, \ast}(t) + H_i^{CHP, \ast}(t) + H_i^{b, \ast}(t)p_y(t) + \beta_i(t)X^*_i(t) \] 
\[ - \alpha_i(t)S_i^*(t) - E^*_i(t)p_{co}(t)) \} \] 
\[ \leq G_i + \mathbb{E}\{A_i(t)(C_{ie}^*(t) - D_{ie}^*(t)) + F_i(t)(C_{iy}^*(t) - D_{iy}^*(t)) \] 
\[ + Z_i(t)(C_{ie}^*(t) - D_{ie}^*(t)) + \sum_{l=1}^{L_i} [I_{il}(t)(D_{iy}^*(t) + d_{iy}^*(t)) \] 
\[ - Y^*_i(t) - D^*_i(t)] + V_i(p_y(t)d^*_i(t) + E^*_i(t)p_e(t) \] 
\[ + (P_i^{CHP, \Pi}(t) + H_i^{CHP, \Pi}(t) + H_i^{b, \Pi}(t)p_y(t) + \beta_i(t)X^*_i(t) \] 
\[ - \alpha_i(t)S_i^*(t) - E^*_i(t)p_{co}(t)) \} \] 
\[ \leq G_i + V_i C_i^{opt} \leq G_i + V_i C_i^{opt} \] 
\[ \text{(E.1)} \]

According to (27) and the stationary randomized policy which achieves the optimal cost \( C_i^{opt} \), the drift-plus-penalty term satisfies

\[ \Delta_i(t) + V_i \mathbb{E}\{C_i(t)\} \leq G_i + V_i C_i^{opt} \leq G_i + V_i C_i^{opt} \] 
\[ \text{(E.2)} \]

Summing across \( t \in \{1, 2, ..., T\} \), the sum term satisfies

\[ \mathbb{E}\{Q_i(T) - Q_i(1)\} + \sum_{t=1}^{T} V_i \mathbb{E}\{C_i(t)\} \leq TG_i + TV_i C_i^{opt} \] 
\[ \text{(E.3)} \]

Dividing both sides by \( TV_i \) and taking \( T \to \infty \), the time average cost term satisfies

\[ \lim_{T \to \infty} \frac{1}{T} \sum_{t=1}^{T} \mathbb{E}\{C_i(t)\} \leq C_i^{opt} + \frac{G_i}{V_i} \] 
\[ \text{(E.4)} \]
References

[1] M. Armendriz, M. Heleno, G. Cardoso, S. Mashayekh, M. Stadler, and L. Nordström, “Coordinated microgrid investment and planning process considering the system operator,” *Applied Energy*, vol. 200, pp. 132–140, 2017.

[2] C. Zhang, J. Wu, Y. Zhou, M. Cheng, and C. Long, “Peer-to-peer energy trading in a microgrid,” *Applied Energy*, vol. 220, pp. 1–12, 2018.

[3] L. Ren, Y. Qin, Y. Li, P. Zhang, B. Wang, P. B. Luh, S. Han, T. Orekan, and T. Gong, “Enabling resilient distributed power sharing in networked microgrids through software defined networking,” *Applied Energy*, vol. 210, pp. 1251–1265, 2017.

[4] Y. Zhu, R. Azim, H. A. Saleem, K. Sun, and R. Sharma, “Microgrid security assessment and islanding control by support vector machine,” in *IEEE PES General Meeting, Denver, CO*, 2015.

[5] X. Zhang, S. Zhu, J. He, B. Yang, and X. Guan, “Credit rating based real-time energy trading in microgrids,” *Applied Energy*, vol. 236, pp. 985–996, 2019.

[6] Y. Guo, J. Wang, H. Chen, G. Li, J. Liu, C. Xu, R. Huang, and Y. Huang, “Machine learning-based thermal response time ahead energy demand prediction for building heating systems,” *Applied Energy*, vol. 221, pp. 16–27, 2018.

[7] M. H. Alobaidi, F. Chebana, and M. A. Meguid, “Robust ensemble learning framework for day-ahead forecasting of household based energy consumption,” *Applied Energy*, vol. 212, pp. 997–1012, 2018.

[8] A. S. Subburaj, B. N. Pushpakaran, and S. B. Bayne, “Overview of grid connected renewable energy based battery projects in usa,” *Renewable and Sustainable Energy Reviews*, vol. 45, pp. 219–234, 2015.
[9] G. Kyriakarakos, A. I. Dounis, S. Rozakis, K. G. Arvanitis, and G. Papadakis, “Polygeneration microgrids: A viable solution in remote areas for supplying power, potable water and hydrogen as transportation fuel,” Applied Energy, vol. 88, pp. 4517–4526, 2011.

[10] M. Little, M. Thomson, and D. Infield, “Electrical integration of renewable energy into stand-alone power supplies incorporating hydrogen storage,” International Journal of Hydrogen Energy, vol. 32, no. 10-11, pp. 1582–1588, 2007.

[11] T. Lipman, J. Edwards, and D. Kammen, “Fuel cell system economics: comparing the costs of generating power with stationary and motor vehicle pem fuel cell systems,” Energy Policy, vol. 32, no. 1, pp. 101–125, 2004.

[12] J. Kissock, “Combined heat and power for buildings using fuel-cell cars,” in International Solar Energy Conference, 1998, pp. 121–132.

[13] A. V. Wijk and L. Verhoef, “Our car as power plant.” Delft University Press, 2014.

[14] A. Fernandes, T. Woudstra, A. V. Wijk, L. Verhoef, and P. V. Aravind, “Fuel cell electric vehicle as a power plant and SOFC as a natural gas reformer: An exergy analysis of different system designs,” Applied Energy, vol. 173, pp. 13–28, 2016.

[15] W. Hou, G. Tian, L. Guo, X. Wang, X. Zhang, and Z. Ning, “Cooperative mechanism for energy transportation and storage in internet of energy,” IEEE Access, vol. 5, pp. 1363–1375, 2017.

[16] W. Tushar, C. Yuen, H. Mohsenian-Rad, T. K. Saha, and K. L. Wood, “Transforming energy networks via peer to peer energy trading: Potential of game theoretic approaches,” IEEE Signal Processing Magazine, vol. 35, no. 4, pp. 90–111, 2018.
[17] N. Liu, X. Yu, W. Fan, C. Hu, T. Rui, Q. Chen, and J. Zhang, “Online energy sharing for nanogrid clusters: a Lyapunov optimization approach,” *IEEE Trans. Smart Grid*, vol. 9, no. 5, pp. 4624–4636, 2018.

[18] N. Liu, M. Cheng, X. Yu, J. Zhong, and J. Lei, “Energy sharing provider for PV prosumer clusters: A hybrid approach using stochastic programming and stackelberg game,” *IEEE Transactions on Industrial Electronics*, vol. 65, no. 8, pp. 6740–6750, 2018.

[19] Y. Chen, W. Wei, F. Liu, Q. Wu, and S. Mei, “Analyzing and validating the economic efficiency of managing a cluster of energy hubs in multi-carrier energy systems,” *Applied Energy*, vol. 230, pp. 403–416, 2018.

[20] N. Liu, X. Yu, W. Cheng, C. Li, and J. Lei, “Energy sharing model with price-based demand response for microgrids of peer-to-peer prosumers,” *IEEE Transactions on Power Systems*, vol. 32, no. 5, pp. 3569–3583, 2017.

[21] T. Lu, Q. Ai, and Z. Wang, “Interactive game vector: A stochastic operation-based pricing mechanism for smart energy systems with coupled-microgrids,” *Applied energy*, vol. 212, pp. 1462–1475, 2018.

[22] Y. Chen, S. Mei, F. Zhou, S. H. Low, W. Wei, and F. Liu, “An energy sharing game in prosumers based on generalized demand bidding: Model and properties,” [https://arxiv.org/abs/1904.07829?context=math](https://arxiv.org/abs/1904.07829?context=math), 04 2019.

[23] N. Liu, X. Yu, C. Wang, and J. Wang, “Energy sharing management for microgrids with pv prosumers: A stackelberg game approach,” *IEEE Transactions on Industrial Informatics*, vol. 13, no. 3, pp. 1088–1098, 2017.

[24] W. Tushar, C. Bo, C. Yuen, D. B. Smith, K. L. Wood, Z. Yang, and H. V. Poor, “Three-party energy management with distributed energy resources in smart grid,” *IEEE Transactions on Industrial Electronics*, vol. 62, no. 4, pp. 2487–2498, 2014.
[25] M. Motalleb, P. Siano, and R. Ghorbani, “Networked stackelberg competition in a demand response market,” Applied Energy, vol. 239, pp. 680–691, 2019.

[26] P. Shamsi, H. Xie, A. Longe, and J. Y. Joo, “Economic dispatch for an agent-based community microgrid,” IEEE Transactions on Smart Grid, vol. 7, no. 5, pp. 2317–2324, 2016.

[27] Y. Wang, W. Saad, Z. Han, H. V. Poor, and T. Baar, “A game-theoretic approach to energy trading in the smart grid,” IEEE Transactions on Smart Grid, vol. 5, no. 3, pp. 1439–1450, 2014.

[28] A. L. Dimeas and N. D. Hatziargyriou, “Operation of a multiagent system for microgrid control,” IEEE Transactions on Power Systems, vol. 20, no. 3, pp. 1447–1455, 2005.

[29] Y. S. F. Eddy, H. B. Gooi, and S. X. Chen, “Multi-agent system for distributed management of microgrids,” IEEE Transactions on Power Systems, vol. 30, no. 1, pp. 24–34, 2014.

[30] L. Jie, Y. Liu, and W. Lei, “Optimal operation for community based multi-party microgrid in grid-connected and islanded modes,” IEEE Transactions on Smart Grid, vol. 9, no. 2, pp. 756–765, 2018.

[31] L. Huang, J. Walrand, and K. Ramchandran, “Optimal demand response with energy storage management,” in IEEE Third International Conference on Smart Grid Communications, 2013.

[32] M. Gatzianas, L. Georgiadis, and L. Tassiulas, “Control of wireless networks with rechargeable batteries,” IEEE Transactions on Wireless Communications, vol. 9, no. 2, pp. 581–593, 2010.

[33] D. Gayme and U. Topcu, “Optimal power flow with distributed energy storage dynamics,” in American Control Conference, 2011.
[34] N. Good, E. A. Martinez Cesena, C. Heltorp, and P. Mancarella, “A trans-active energy modelling and assessment framework for demand response business cases in smart distributed multi-energy systems,” Energy, vol. 184, pp. 165–179, 2019.

[35] C. Battistelli, “Generalized microgrid-to-smart grid interface models for vehicle-to-grid,” in Innovative Smart Grid Technologies (ISGT), 2013 IEEE PES, 2013.

[36] H. M. Khodr, N. E. Halabi, and M. Garca-Gracia, “Intelligent renewable microgrid scheduling controlled by a virtual power producer: A laboratory experience,” Renewable Energy, vol. 48, no. 48, pp. 269–275, 2012.

[37] K. Shinoda, E. P. Lee, M. Nakano, and Z. Lukszo, “Optimization model for a microgrid with fuel cell vehicles,” in IEEE International Conference on Networking, 2016.

[38] L. B. Jaramillo and A. Weidlich, “Optimal microgrid scheduling with peak load reduction involving an electrolyzer and flexible loads,” Applied Energy, vol. 169, pp. 857–865, 2016.

[39] M. Petrollese, L. Valverde, D. Cocco, G. Cau, and J. Guerra, “Real-time integration of optimal generation scheduling with MPC for the energy management of a renewable hydrogen-based microgrid,” Applied Energy, vol. 166, pp. 96–106, 2016.

[40] N. Chiesa, M. Korps, O. E. Kongstein, and A. degrd, “Dynamic control of an electrolyser for voltage quality enhancement,” in Proc. Int. Conf. on Power System Transients (IPST-11), 2011.

[41] S. Lakshminarayana, T. Quek, and H. Poor, “Cooperation and storage tradeoffs in power grids with renewable energy resources,” IEEE Journal on Selected Areas in Communications, vol. 32, no. 7, pp. 1386–1397, 2014.
[42] G. Sarthak, K. Vassilis, and S. Walid, “Optimal real-time coordination of energy storage units as a voltage-constrained game,” *IEEE Transactions on Smart Grid*, vol. 10, no. 4, pp. 3883–3894, 2019.

[43] L. Georgiadis, M. J. Neely, and L. Tassiulas, “Resource allocation and cross-layer control in wireless networks,” *Foundations and Trends in Networking*, vol. 1, no. 1, pp. 1–144, 2006.

[44] U. Kant and D. Grosu, “Double auction protocols for resource allocation in grids,” in *International Conference on Information Technology: Coding and Computing*, 2005.

[45] “pjm hourly load,” https://dataminer2.pjm.com/feed/hrl_load_metered, 2018.

[46] “Renewables.ninja,” https://www.renewables.ninja, 2018.

[47] “Power smart pricing served by ameren illinois,” http://www.powersmartpricing.org/prices/, 2018.

[48] F. Alavi, E. Park Lee, N. van de Wouw, B. De Schutter, and Z. Lukszo, “Fuel cell cars in a microgrid for synergies between hydrogen and electricity networks,” *Applied Energy*, vol. 192, pp. 296–304, 2017.

[49] K. Zhou, J. Pan, and L. Cai, “Indirect load shaping for CHP systems through real-time price signals,” *IEEE Transactions on Smart Grid*, vol. 7, no. 1, pp. 282–290, 01 2016.