Optimal Charging Control of Energy Storage and Electric Vehicle of an Individual in the Internet of Energy with Energy Trading

Chun-Cheng Lin, Der-Jiunn Deng*, Chih-Chi Kuo, and Yu-Lin Liang

Abstract—**Developing green energy to be applied in green cities has received much attention. The Internet of energy (IoE) effectively improves networking of distributed green energies through extending smart grids with bi-directional transmission of energy and distributed renewable energy facilities. Previous works on the IoE focused on decisions of IoE operators or optimization of the whole system. However, few considered optimal decisions of a single end-user in the IoE. Therefore, this work creates a mixed-integer linear programming (MILP) model for a single end-user that considers green energy generation, an energy storage, an electric vehicle, and an IoE-based energy trading platform to reduce energy waste. This model considers a complete system of charging control of multiple facilities of a single end-user in the IoE, and allows the end-user to purchase energy and sell green energy through the IoE, in which the energy prices of the electrical grid and the IoE platform are set by the power company and the energy market, respectively. Because MILP is NP-complete and the proposed model involves a large number of variables and constraints, this work further proposes a genetic algorithm for this problem, in which a repairing scheme is proposed to handle solution infeasibility of all constraints. By simulation, the proposed algorithm is verified to effectively reduce energy waste.**

Index Terms—**Internet of energy, energy trading, battery energy storage system, real-time price, electric vehicle**

I. INTRODUCTION

In a green city, city development has been based on environmental protection and sustainability, including green transportation networks, comprehensive resource recovery systems, reuse of water resources, effective urban space planning, use of renewable energy, and efficient electricity transmission network. Various studies on energy distribution and generation methods in green cities have been widely studied. Among them, the Internet of energy (IoE) incorporates the Internet of things (IoT) with energy to distribute energy and transmit information. The IoE will be implemented in near future green cities [1]. All energies (including green/renewable energies) and end-users are connected together through the IoE; and energy suppliers and demanders communicate tightly in real time through the IoE to adjust generation, saving, and distribution of energy sources. The goal of the IoE is to raise the utilization rate of energy, emphasize priority of using renewable energies, and introduce distributed energies with diversity to satisfy demand of the overall energy market. As the IoE emerges, the energy market relies more and more on distributed renewable energy generation facilities in electrical grids. An end-user can consume energy from original electrical grids and other distributed renewable energies in the same grid, to relieve the power generation pressure of energy suppliers in original electrical grids and even become an energy supplier.

Most of the previous works on the IoE or related energy decisions focused on the optimal decisions of the IoE operators or the optimization of the whole system, e.g., taking all end-users as a group to control the timing of charging energy to shift the peak energy load [2]. In addition, pervious works on IoE did not concurrently investigate the decisions of battery energy storage systems (BESS), real-time price (RTP), and electric vehicles (EVs) [3], e.g., only BESSs on an energy trading platform [4], distribution of renewable energy facilities and BESSs [5], and setting RTP [6]. However, few of the previous works investigated the optimal decision of a single end-user in the IoE.

As a result, this work considers an IoE system for a single end-user (household) in a green city (Fig. 1), in which the end-user has solar panels, a wind turbine, an energy storage (ES), and an EV; and an IoE-based energy trading platform allows the end-user to trade energy with other end-users. Under such a system, this work establishes a mixed-integer linear programming (MILP) model to optimize the charging/discharging decisions of multiple facilities of this end-user. In general, MILP is NP-complete. To solve the proposed model with a lot of variables and constraints, this work further proposes a genetic algorithm (GA) with a repairing scheme to cope with solution infeasibility of all constraints. Finally, the proposed algorithm is implemented and verified via simulation.

The main contributions of this work are as follows: 1) This work is the first to investigate the optimal decision of a single end-user to decide whether to charge or discharge the ES and the EV in the IoE. 2) The model concurrently considers the energy market price from the energy trading platform and the

Manuscript received September 1, 2017; revised November 5, 2017; accepted November 23, 2017. This work was supported in part by Grant MOST 106-2221-E-009-101-MY3.

C.-C. Lin, C.-C. Kuo, and Y.-L. Liang are with Department of Industrial Engineering and Management, National Chiao Tung University, Hsinchu 300, Taiwan. E-mails: cclin321@nctu.edu.tw, berbejuice@gmail.com, fssh5128@gmail.com.

D.-J. Deng is with Department of Computer Science and Information Engineering, National Changhua University of Education, Changhua 500, Taiwan. E-mail: djdeng@cc.ncue.edu.tw

* D.-J. Deng is the corresponding author of this paper.

RTP from the power company to make decisions. 3) In the IoE model, the end-user can adopt the ES, the EV, and renewable energy generating facilities to reduce grid energy waste.

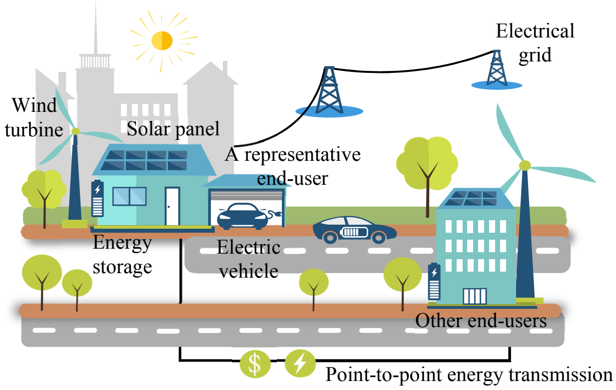

Fig. 1. Illustration of multiple facilities of an end-user in a green city.

II. PRELIMINARIES

A. System Framework

Consider a city deployed with an IoE-based distributed energy distribution system. The IoE is an Internet-based electrical grid of multiple facilities, and the energy can be transmitted freely between any two facilities. The facilities concerned in the IoE include 1) grid energy generating facilities of the power company; and 2) solar panels and wind turbines, 3) EVs, 4) household electrical equipment (HEE), and 5) ESs of end-users (Fig. 2). In addition, an energy trading platform allows end-users to trade energy.

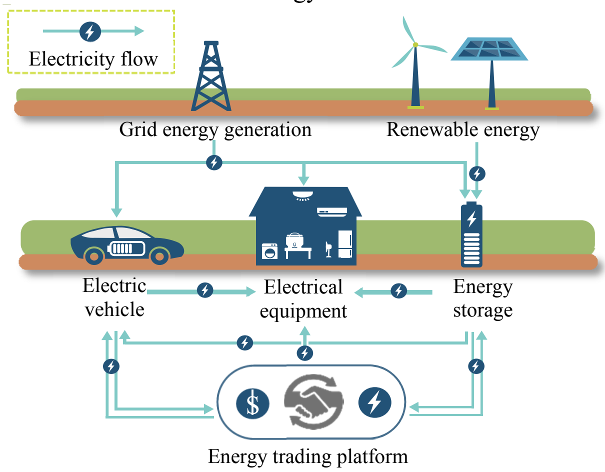

Fig. 2. Electricity flow in the proposed model.

Assumptions of the system for an end-user are as follows. There are three energy sources: electrical grid energy, PV energy, and wind energy. The grid energy is generated by the power company; and the end-user has solar panels and a wind turbine to generate renewable energy. In addition, the end-user has some HEE, an ES, and an EV.

The HEE consumes energy differently on weekdays and weekends. Suppose that the end-user stays at home; therefore, the energy consumption in a weekend is higher than that in a weekday. The ES has a battery to be charged and discharged efficiently. Suppose that the renewable energy generated per day is fixed, and can only be stored in the ES.

The EV is a battery EV [7]. For simplicity, the end-user goes to work in the daytime of each weekday, during which the vehicle cannot be charged nor discharged in the house. Suppose that the energy demand of each weekday is the same, and is zero in weekends. The EV can be regarded as a mobile ES. The energy stored in the EV supplies usage of the vehicle and the HEE, or is sold to other end-users.

Both ESs and EV play the role of energy demanders and suppliers concurrently. For simplicity, suppose that the EV and the ES cannot be concurrently charged and discharged. In addition, energy is not consumed during transmission. The ES and the EV have energy conversion loss rates. The EV cannot discharge too much. The hourly energy RTP is set according to the energy demand by the power company. Suppose that the end-user receives the hourly RTP of the previous day in advance to make decision of this day.

B. Related work

In smart grids [8], energy suppliers collect real-time energy demand of end-users through smart meters, and transmit the information on energy amount, energy price, and energy interrupt to end-users [9]. Table 1 shows a classification of recent works on reducing energy waste of electrical grids through various DSM (demand-side management) strategies, e.g., using the RTP, BESSs, and energy trading. The works in [10], [11], [12] investigated whether RTP can reduce the energy waste of end-users. Aside from RTP, the work in [13] additionally considered EVs to investigate the economic feasibility when household EVs provide flexible energy demand, through the price signals in smart grids, to reduce costs of energy usage of EVs. The works in [4] and [14] concurrently considered both RTP and BESSs. The work in [14] compared the peak load of the electrical grids with and without BESSs when RTP is considered. In [4], the energy in BESSs can be traded in the energy market directly. To maximize utilization of the electrical grid, BESS is charged when the energy price is low; and sells it when the energy price is high. The works in [15] and [16] discussed only BESS. The work in [15] proposed a mathematical model with BESS, which adopts an interior point method to obtain the optimal solution of charging and discharging. The work in [16] employed BESSs to reduce the peak load, and compared the results of three kinds of BESS sizes. The work in [5] compared the different discharging strategies of grid-connected residential PV systems with BESSs, and considered a model that remotely controls the discharging condition, maximizes the self-energy consumption, and reduces the highest energy price level of one day to decrease the energy load of the electrical grid. The work in [17] investigated a facility location problem that concurrently considers BESSs, renewable energy facilities, and charging stations of EVs.

Energy systems have experienced four stages since they were invented in the second industrial revolution period, and the IoE is in the fourth stage [18]. The main difference of smart grids and the IoE is that the IoE emphasizes renewable energy and point-to-point transactions. In the IoE with bi-directional transmissions, the households that generate renewable energy can trade their respective remaining energy with each other through machine-to-machine communications [19], [20]. The work in [21] employed the Nash bargaining theory to simulate an energy trading market, and simulation showed that 13.2% of the total cost of the whole IoE system can be reduced. The work in [22] simulate the distribution of charging stations of EVs to improve utilization of renewable energy in the IoE.

TABLE 1. Classification of recent works.

Reference	RTP	BESS	EV	Energy trading	Renewable energy
[10]-[12]	v				
[13]	v		v		
[4], [14]	v	v			
[15], [16]		v			
[5]		v			v
[17]		v	v		v
[21]		v		v	v
[22]			v		v
[2], [23]	v	v		v	v
Our	v	v	v	v	v

The work in [2] had applied the strategies of RTP, BESS, and energy trading to shift the peak load of the electric grid. This work additionally considers an EV to consider the optimal decisions of a single end-user in the IoE. Although the work in [23] also considered the optimal decision of a single end-user, it did not consider the energy trading among end-users.

III. MATHEMATICAL MODEL

This work considers hourly decisions of multiple facilities of a single end-user for one day in the IoE system described above to minimize the total energy usage cost. The HEE of the end-user is charged from four sources (i.e., grid energy, the energy stored in the ES as well as the EV, and the energy purchased from other end-users). The ES is charged from two sources (i.e., grid energy and the energy purchased from other end-users). The EV is charged from three sources (i.e., grid energy, the energy stored in the ES, and the energy purchased from other end-users). Two ESs (i.e., the ES and the EV) are sold to other end-users. Therefore, this model includes 11 decision variables to decide the above four types of energy flows. The model also considers two binary decision variables to decide whether the ES and the EV are charged or discharged. For 24 hours of one day, this model has 13×24 decision variables. Notations used in the model is given in Table 2.

The MILP model for the concerned problem is detailed as follows. The objective of the problem is to minimize the total cost of an end-user in one day *i* as represented as follows:

$$\text{Minimize} \quad C^i_{\text{grid}} + C^i_{\text{user}} - R^i_{\text{store}} \tag{1}$$

Each item of the above objective is enforced to be calculated by the following constraints. The constraint of calculating the total grid energy usage cost C^i_{grid} of the end-user in day *i* is as follows:

$$C^i_{\text{grid}} = \sum_{t=1}^{24} RTP_i(t) \cdot [E^i_{\text{uug}}(t) + \frac{E^i_{\text{sfg}}(t)}{1-\beta_{\text{store}}} + \frac{E^i_{\text{vfg}}(t)}{1-\beta_{\text{ev}}}] \tag{2}$$

TABLE 2. Notations used in the model.

Parameter	Definition
t^i_{on}	Beginning o'clock of working hours in day *i*.
t^i_{off}	Ending o'clock of working hours in day *i*.
$E^i_{\text{vehicle}}(0)$	Initial energy amount stored in the EV in day *i*, i.e., the final energy amount of the EV in the previous day.
$E^i_{\text{storage}}(0)$	Initial energy amount stored in the ES in day *i*.
$P^i(t)$	Energy price for the *t*th hour of day *i* in the trading market.
$E^i_{\text{res}}(t)$	Total amount of renewable energy generated for the *t*th hour of day *i*.
$E^i_{\text{pv}}(t)$	The energy amount generated by the solar panels for the *t*th of day *i*.
$E^i_{\text{wind}}(t)$	The energy amount generated by the wind turbine for the *t*th of day *i*.
$E^{\max}_{\text{store}}$	Capacity of the ES, i.e., the maximal energy amount that can be stored in the facility.
$E^{\max}_{\text{ev}}$	Maximal energy amount that can be stored by the EV.
$D^i_{\text{ev}}(t)$	Energy demand amount of the EV for the *t*th hour of day *i*.
$E^{\text{low}}_{\text{limit}}$	Minimal energy amount that avoids the EV from being fully discharged to damage it permanently.
$E^{\text{low}}_{\text{ev}}$	Minimal energy amount for driving the EV for one day, $E^{\text{low}}_{\text{ev}} = \sum_{t=1}^{24} D^i_{\text{ev}}(t) + E^{\text{low}}_{\text{limit}}$.
β_{store}	Energy conversion loss rate of the ES.
β_{ev}	Energy conversion loss rate of the EV.
$RATE_{\text{store}}$	Maximal charge amount of the ES per hour.
$RATE_{\text{ev}}$	Maximal charge amount of the EV per hour.
$RTP_i(t)$	RTP of the energy supplied by the power company for the *t*th hour of day *i*.
$D^i_{\text{user}}(t)$	Energy demand amount of the HEE of the end-user for the *t*th hour of day *i*.
$\theta^i_{\text{work}}(t)$	A binary variable of deciding if the *t*th hour of day *i* is a working hour as follows: $\theta^i_{\text{work}}(t) = \begin{cases} 1, & \text{if } i < 6 \text{ and } t \in \{t^i_{\text{on}}, t^i_{\text{on}}+1, ..., t^i_{\text{off}}-1\}; \\ 0, & \text{otherwise.} \end{cases}$
Decision variable	**Definition**
$E^i_{\text{uug}}(t)$	The grid energy amount purchased for usage of the HEE (end-user) for the *t*th hour of day *i*, in which the subscript of the variable abbreviates user-use-grid.
$E^i_{\text{sfg}}(t)$	The grid energy amount purchased for charging the ES for the *t*th hour of day *i*, in which the subscript of the variable abbreviates storage-from-grid.
$E^i_{\text{vfg}}(t)$	The grid energy amount purchased for charging the EV for the *t*th hour of day *i*, in which the subscript of the variable abbreviates vehicle-from-grid.
$E^i_{\text{uus}}(t)$	The energy amount in the ES used by the HEE for the *t*th hour of day *i*, in which the subscript of the variable abbreviates user-use-storage.
$E^i_{\text{uuv}}(t)$	The energy amount stored in the EV that is used by the HEE for the *t*th hour of day *i*.
$E^i_{\text{vfs}}(t)$	The energy amount stored in the ES that is used by the EV for the *t*th hour of day *i*.
$E^i_{\text{sso}}(t)$	The energy amount stored in the ES that is sold to other end-users in the IoE for the *t*th hour of day *i*, in which the subscript of the variable abbreviates storage-sold-others.
$E^i_{\text{vso}}(t)$	The energy amount stored in the EV that is sold to other end-users for the *t*th hour of day *i*.
$E^i_{\text{sfo}}(t)$	The energy amount purchased from other end-users in the IoE to charge the ES for the *t*th hour of day *i*.
$E^i_{\text{vfo}}(t)$	The energy amount purchased from other end-users in the IoE to charge the EV for the *t*th hour of day *i*.
$E^i_{\text{ubo}}(t)$	The energy amount purchased from other end-users to be used by the HEE for the *t*th hour of day *i*.
$\theta^i_{\text{s}}(t)$	A binary variable of deciding whether the ES is charged or discharged for the *t*th hour of day *i*.
$\theta^i_{\text{ev}}(t)$	A binary variable of deciding whether the EV is charged or discharged for the *t*th hour of day *i*.

Note that energy conversion of the latter two items has loss, so each of them are divided by an energy conversion loss factor.

The constraint of calculating the cost C_{user}^i of purchasing energy from energy trading in day i is as follows:

$$C_{\text{user}}^i = \sum_{t=1}^{24} P^i(t) \cdot [E_{\text{ubo}}^i(t) + \frac{E_{\text{sfo}}^i(t)}{1-\beta_{\text{store}}} + \frac{E_{\text{vfo}}^i(t)}{1-\beta_{\text{ev}}}] \tag{3}$$

The constraint of calculating the total revenue R_{store}^i of the end-user for saving and selling energy in day i is as follows:

$$\begin{aligned} R_{\text{store}}^i = & \sum\nolimits_{t=1}^{24} RTP^i(t) \cdot [E_{\text{uus}}^i(t) + E_{\text{uuv}}^i(t)] \\ & + \sum\nolimits_{t=1}^{24} P^i(t) \cdot [E_{\text{sso}}^i(t) + E_{\text{vso}}^i(t)] \end{aligned} \tag{4}$$

The total amount of renewable energy generated for the tth hour of day i ($E_{\text{res}}^i(t)$) is the sum of the solar panels ($E_{\text{pv}}^i(t)$) and the wind turbine ($E_{\text{wind}}^i(t)$) for this hour as follows:

$$E_{\text{res}}^i(t) = E_{\text{pv}}^i(t) + E_{\text{wind}}^i(t), \qquad \forall t = 1,2,...,24 \tag{5}$$

Next, the constraints in the model are introduced. First, consider constraints for the ES. The energy amount $E_{\text{storage}}^i(t)$ stored in the ES at the end of the tth hour of day i must be no greater than the maximal capacity $E_{\text{store}}^{\max}$ as follows:

$$E_{\text{storage}}^i(t) \le E_{\text{store}}^{\max}, \qquad \forall t = 1,2,...,24 \tag{6}$$

Except from the renewable energy, the ES cannot be charged and discharged by other energies at the same time. Hence, let $\theta_{\text{s}}^i(t)$ denote a binary decision variable of deciding whether the ES is charged or discharged for the tth hour of day i, and use it to control this requirement as follows:

$$E_{\text{sfg}}^i(t) + E_{\text{sfo}}^i(t) \le M\theta_{\text{s}}^i(t), \qquad \forall t = 1,2,...,24 \tag{7a}$$

$$E_{\text{uus}}^i(t) + E_{\text{sso}}^i(t) + E_{\text{vfs}}^i(t) \le M(1-\theta_{\text{s}}^i(t)), \qquad \forall t = 1,2,...,24 \tag{7b}$$

$$\theta_{\text{s}}^i(t) \in \{0,1\}, \qquad \forall t = 1,2,...,24 \tag{7c}$$

where M is a large number.

Next, consider the constraints when the ES purchases and sells energy through energy trading. From the purchasing aspect, the total amount of the energy stored by the ES from other end-users ($E_{\text{sfo}}^i(t)$), the electrical grid ($E_{\text{sfg}}^i(t)$), and the renewable energy system ($E_{\text{res}}^i(t)$) for the tth hour of day i must be no more than the remaining capacity of the ES ($E_{\text{store}}^{\max} - E_{\text{storage}}^i(t-1)$) as follows:

$$E_{\text{sfo}}^i(t) + E_{\text{sfg}}^i(t) + E_{\text{res}}^i(t) \le E_{\text{store}}^{\max} - E_{\text{storage}}^i(t-1), \forall t = 1,2,...,24 \tag{8}$$

From the selling aspect, the total energy amount to which the ES to be used by other end-users ($E_{\text{sso}}^i(t)$), the HEE ($E_{\text{uus}}^i(t)$), and the EV ($E_{\text{vfs}}^i(t)$) for the tth hour of day i must be no more than the amount of the energy stored in the ES at the end of the previous hour ($E_{\text{storage}}^i(t-1)$), as follows:

$$E_{\text{sso}}^i(t) + E_{\text{uus}}^i(t) + E_{\text{vfs}}^i(t) \le E_{\text{storage}}^i(t-1), \qquad \forall t = 1,2,...,24 \tag{9}$$

With the above constraints from the purchasing and selling aspects, the amount of the energy stored in the ES at the end of each hour ($E_{\text{storage}}^i(t)$) must be the amount at the end of the previous hour ($E_{\text{storage}}^i(t-1)$) deducted from the energy amount from the selling aspect added to the energy amount from the purchasing aspect, as follows:

$$\begin{aligned} E_{\text{storage}}^i(t) = & E_{\text{storage}}^i(t-1) - E_{\text{uus}}^i(t) - E_{\text{vfs}}^i(\text{t}) - E_{\text{sso}}^i(t) \\ & + E_{\text{sfg}}^i(t) + E_{\text{res}}^i(t) + E_{\text{sfo}}^i(t), \qquad \forall t=1,2,...,24 \end{aligned} \tag{10}$$

When $t = 1$, $E_{\text{storage}}^i(t-1) = E_{\text{storage}}^i(0) = E_{\text{storage}}^{i-1}(24)$, which is the final energy amount of the storage in the previous day.

In real world, the hourly charge and discharge amounts of the ES have a maximal bound $RATE_{\text{store}}$, as follows:

$$\begin{aligned} & E_{\text{sfo}}^i(t), E_{\text{sfg}}^i(t), E_{\text{sso}}^i(t), E_{\text{uus}}^i(t), E_{\text{vfs}}^i(t) \le RATE_{\text{store}}, \\ & \qquad \forall t=1,2,...,24 \end{aligned} \tag{11}$$

Next, consider constraints for the EV. We have upper and lower bounds for the energy amount stored at the end of the tth hour of day i by the EV ($E_{\text{vehicle}}^i(t)$), respectively, as follows:

$$E_{\text{vehicle}}^i(t) \le E_{\text{ev}}^{\max}; E_{\text{ev}}^{\text{low}} \le E_{\text{vehicle}}^i(t), \qquad \forall t = 1,2,...,24 \tag{12}$$

Similar to (7a)-(7c) for the ES, the EV cannot be charged and discharged by other energies at the same time, but the constraints for the EV consider different energy sources as follows:

$$E_{\text{vfg}}^i(t) + E_{\text{vfs}}^i(t) + E_{\text{vfo}}^i(t) \le M \cdot \theta_{\text{ev}}^i(t), \qquad \forall t = 1,2,...,24 \tag{13a}$$

$$E_{\text{uuv}}^i(t) + E_{\text{vso}}^i(t) \le M(1-\theta_{\text{ev}}^i(t)), \qquad \forall t = 1,2,...,24 \tag{13b}$$

$$\theta_{\text{ev}}^i(t) \in \{0,1\}, \qquad \forall t = 1,2,...,24 \tag{13c}$$

Similar to (8) for the ES, the purchasing aspect of the EV in the IoE is restricted, but considers different energy sources as follows:

$$E_{\text{vfg}}^i(t) + E_{\text{vfs}}^i(t) + E_{\text{vfo}}^i(t) \le E_{\text{ev}}^{\max} - E_{\text{vehicle}}^i(t-1), \forall t = 1,2,...,24 \tag{14}$$

Similar to (9) for the ES, the selling aspect of the EV in the

IoE is restricted, but considers different energy sources as follows:

$$E^i_{\text{uuv}}(t) + E^i_{\text{vso}}(t) \le E^i_{\text{vehicle}}(t-1) - E^{\text{low}}_{\text{ev}}, \qquad \forall t = 1,2,...,24 \quad (15)$$

In addition, recall that the EV is assumed to be charged only at the end-user's house. Hence, when the end-user is working (i.e., the EV is at the working place), the EV must be not able to be charged, as follows:

$$E^i_{\text{vfg}}(t) + E^i_{\text{vfs}}(t) + E^i_{\text{vfo}}(t) + E^i_{\text{uuv}}(t) + E^i_{\text{vso}}(t) \le M(1-\theta^i_{\text{work}}(t)), \quad \forall t = 1,2,...,24 \quad (16a)$$

$$\theta^i_{\text{work}}(t) \in \{0,1\}, \qquad \forall t = 1,2,...,24 \quad (16b)$$

When the EV is at the working place (i.e., $\theta^i_{\text{work}}(t) = 1$), all variables on the left side in (16a) must be zero.

Similar to (10) for the ES, with the above constraints of the EV from the purchasing and selling aspects, the amount of the energy stored in the ES at the end of each hour ($E^i_{\text{vehicle}}(t)$) can be characterized, but considers different energy sources as follows:

$$E^i_{\text{vehicle}}(t) = E^i_{\text{vehicle}}(t-1) + E^i_{\text{vfg}}(t) + E^i_{\text{vfs}}(t) + E^i_{\text{vfo}}(t) - E^i_{\text{uuv}}(t) - E^i_{\text{vso}}(t), \qquad \forall t = 1,2,...,24 \quad (17)$$

Similar to (11) for the ES, the charge and discharge amounts of the EV have a maximal bound $RATE_{\text{ev}}$, but have different energy sources as follows:

$$E^i_{\text{vfg}}(t), E^i_{\text{vfs}}(t), E^i_{\text{vfo}}(t), E^i_{\text{vso}}(t), E^i_{\text{uuv}}(t) \le RATE_{\text{store}}, \qquad \forall t=1,2,...,24 \quad (18)$$

After considering constraints for the ES and the EV, the constraint for the energy demand of the HEE ($D^i_{\text{user}}(t)$) is considered as follows:

$$E^i_{\text{uug}}(t) + E^i_{\text{uus}}(t) + E^i_{\text{ubo}}(t) + E^i_{\text{uuv}}(t) = D^i_{\text{user}}(t), \qquad \forall t = 1,2,...,24 \quad (19)$$

In the above constraint, the energy demand of the HEE ($D^i_{\text{user}}(t)$) must be the sum of the energy from the electrical grid ($E^i_{\text{uug}}(t)$), the energy stored in the ES ($E^i_{\text{uus}}(t)$), the energy purchased from the other end-users ($E^i_{\text{ubo}}(t)$), and the energy stored in the EV ($E^i_{\text{uuv}}(t)$). Finally, all decision and response variables except for binary ones must be no less than zero.

Note that if the amounts of the renewable energy and the energy demand per hour are dynamic in the real situation, the proposed model can easily be applied by just simply adding an index to the variable for the renewable energy and considering the detailed real daily work shift of the end-user.

IV. THE PROPOSED ALGORITHM

Because MILP is NP-complete and the proposed model involves a large number of variables and constraints, this work further proposes a GA [24] for this problem. The GA starts with a population of random feasible candidate solutions (CSs) by Algorithm 1, and evaluates the performance of each CS by a cost function. A number of parent CSs are selected by roulette wheel selection or tournament selection. Each pair of parent CSs generates offspring CSs through some evolutionary operators, e.g., crossover and mutation. However, the offspring CSs generated may not be feasible, and hence are repaired to be feasible by sequentially calling Algorithms 2, 3, 4, and 5 taking τ as the argument for each τ = 1, 2, .., 24. Then, the offspring CSs with better cost than some parent CSs are selected to replace the parent CSs. Repeat the above procedure until the maximal number of iterations is achieved.

Algorithm 1 GenerateOneFeasibleCS()

for τ = 1, 2, …, 24 **do**
  All gene values at hour τ in this CS are set to 0
  $\theta^i_{\text{s}}(\tau) = \text{rndInt}(0,1)$ and $\theta^i_{\text{ev}}(\tau) = \text{rndInt}(0,1)$
  if $\theta^i_{\text{s}}(\tau) = 1$ **then**
    $E^i_{\text{sfg}}(\tau) = \text{rnd}(0, \min(E^{\max}_{\text{store}} - E^i_{\text{storage}}(\tau) - E^i_{\text{res}}(\tau), RATE_{\text{store}}))$
    $E^i_{\text{sfo}}(\tau) = \text{rnd}(0, \min(E^{\max}_{\text{store}} - E^i_{\text{storage}}(\tau) - E^i_{\text{sfg}}(\tau) - E^i_{\text{res}}(\tau), RATE_{\text{store}}))$
  else
    $E^i_{\text{uus}}(\tau) = \text{rnd}(0, \min(D^i_{\text{user}}(\tau), \min(E^i_{\text{storage}}(\tau), RATE_{\text{store}})))$
    $E^i_{\text{sso}}(\tau) = \text{rnd}(0, \min(E^i_{\text{storage}}(\tau) - E^i_{\text{uus}}(\tau), RATE_{\text{store}}))$
  end if
  if $\theta^i_{\text{work}}(\tau) = 0$ **then**
    if $\theta^i_{\text{ev}}(\tau) = 1$ **then**
      if $\theta^i_{\text{s}}(\tau) = 0$ **then** $E^i_{\text{vfs}}(\tau) = \text{rnd}(0, \min(E^{\max}_{\text{ev}} - E^i_{\text{vehicle}}(\tau), E^i_{storage}(\tau) - E^i_{sso}(\tau) - E^i_{uus}(\tau), RATE_{\text{ev}}))$ **end if**
      $E^i_{\text{vfg}}(\tau) = \text{rnd}(0, \min(E^{\max}_{\text{ev}} - E^i_{\text{vehicle}}(\tau) - E^i_{\text{vfs}}(\tau), RATE_{\text{ev}}))$
      $E^i_{\text{vfo}}(\tau) = \text{rnd}(0, \min(E^{\max}_{\text{ev}} - E^i_{\text{vehicle}}(\tau) - E^i_{\text{vfs}}(\tau) - E^i_{\text{vfg}}(\tau), RATE_{\text{ev}}))$
    else
      $E^i_{\text{uuv}}(\tau) = \text{rnd}(0, \min(D^i_{\text{user}}(\tau) - E^i_{\text{uus}}(\tau), E^i_{\text{vehicle}}(\tau) - E^{\text{low}}_{\text{ev}}(\tau), RATE_{\text{ev}}))$
      $E^i_{\text{vso}}(\tau) = \text{rnd}(0, \min(E^i_{\text{vehicle}}(\tau) - E^{\text{low}}_{\text{ev}}(\tau) - E^i_{\text{uuv}}(\tau), RATE_{\text{ev}}))$
    end if
  end if
  $E^i_{\text{uug}}(\tau) = \text{rnd}(0, D^i_{\text{user}}(\tau) - E^i_{\text{uuv}}(\tau) - E^i_{\text{uus}}(\tau))$
  $E^i_{\text{ubo}}(\tau) = D^i_{\text{user}}(\tau) - E^i_{\text{uuv}}(\tau) - E^i_{\text{uus}}(\tau) - E^i_{\text{uug}}(\tau)$
  Compute $E^i_{\text{storage}}(\tau)$ by (10) and $E^i_{\text{vehicle}}(\tau)$ by (17)
end for

The main components of the GA are introduced as follows.

A. Solution encoding and cost evaluation

A CS must encode the 13 decision variables in Table 2 for 24 hours. Therefore, a CS in this work is encoded as the following 13 × 24 = 312 variable values: 〈 $E^i_{\text{uug}}(1)$, $E^i_{\text{sfg}}(1)$, $E^i_{\text{vfg}}(1)$,

$E^i_{\mathrm{uus}}(1)$, $E^i_{\mathrm{uuv}}(1)$, $E^i_{\mathrm{vfs}}(1)$, $E^i_{\mathrm{sso}}(1)$, $E^i_{\mathrm{vso}}(1)$, $E^i_{\mathrm{sfo}}(1)$, $E^i_{\mathrm{vfo}}(1)$, $E^i_{\mathrm{ubo}}(1)$, $\theta^i_{\mathrm{s}}(1)$, $\theta^i_{\mathrm{ev}}(1)$ | $E^i_{\mathrm{uug}}(2)$, $E^i_{\mathrm{sfg}}(2)$, …, $\theta^i_{\mathrm{ev}}(2)$ | … | $E^i_{\mathrm{uug}}(24)$, $E^i_{\mathrm{sfg}}(24)$, …, $\theta^i_{\mathrm{ev}}(24)\rangle$.

The performance of a CS is evaluated by a cost function, which is equal to the total cost of an end-user in one day *i* in Objective (1), in which the three items can be calculated by (2)–(4).

The proposed GA keeps feasibility of all CSs, and hence generates initial CSs that must be feasible. Hence, Algorithm 1 is proposed to generate an initial feasible CS.

B. Repairing infeasible CSs

In the GA, crossover could lead to violation of Constraints (8) , (9), (14), and (15); and mutation that mutate the values of $\theta^i_{\mathrm{s}}(\tau)$ and $\theta^i_{\mathrm{ev}}(\tau)$, so that Constraints (7a)–(7c) and (13a)–(13a) could be violated. Therefore, in the proposed GA, each iteration of the algorithm always maintains feasibility of all CSs. Therefore, the feasibility of each CS is checked. If the CS is infeasible, it is repaired to be feasible. The algorithms of repairing infeasible CSs are given in Algorithms 2, 3, 4, and 5, which are detail as follows.

Algorithm 2 checks feasibility of Constraints (7a)–(7c), which avoid the ES from being charged and discharged at the same time. Algorithm 3 checks feasibility of Constraints (13a)–(13a), which avoid the EV from being charged and discharged at the same time.

Algorithm 2 RepairStorageBeChargedAtSameTime(hour τ)

if $\theta^i_{\mathrm{s}}(\tau)=0$ **then**
  if $E^i_{\mathrm{sfg}}(\tau)>0$ **then** $E^i_{\mathrm{sfg}}(\tau)=0$
  if $E^i_{\mathrm{sfo}}(\tau)>0$ **then** $E^i_{\mathrm{sfo}}(\tau)=0$
else
  if $E^i_{\mathrm{uus}}(\tau)>0$ **then** $E^i_{\mathrm{uug}}(\tau)=E^i_{\mathrm{uug}}(\tau)+E^i_{\mathrm{uus}}(\tau)$ and then $E^i_{\mathrm{uus}}(\tau)=0$
  if $E^i_{\mathrm{sso}}(\tau)>0$ **then** $E^i_{\mathrm{sso}}(\tau)=0$
  if $E^i_{\mathrm{vfs}}(\tau)>0$ **then** $E^i_{\mathrm{vfg}}(\tau)=E^i_{\mathrm{vfg}}(\tau)+E^i_{\mathrm{vfs}}(\tau)$ and then $E^i_{\mathrm{vfs}}(\tau)=0$
end if

Algorithm 3 RepairVehicleBeChargedAtSameTime(hour τ)

if $\theta^i_{\mathrm{ev}}(\tau)=0$ **then**
  if $E^i_{\mathrm{vfg}}(\tau)>0$ **then** $E^i_{\mathrm{vfg}}(\tau)=0$
  if $E^i_{\mathrm{vfs}}(\tau)>0$ **then** $E^i_{\mathrm{sso}}(\tau)=E^i_{\mathrm{sso}}(\tau)+E^i_{\mathrm{vfs}}(\tau)$ and then $E^i_{\mathrm{vfs}}(\tau)=0$
  if $E^i_{\mathrm{vfo}}(\tau)>0$ **then** $E^i_{\mathrm{vfo}}(\tau)=0$
else
  if $E^i_{\mathrm{uuv}}(\tau)>0$ **then** $E^i_{\mathrm{uug}}(\tau)=E^i_{\mathrm{uug}}(\tau)+E^i_{\mathrm{uuv}}(\tau)$ and then $E^i_{\mathrm{uuv}}(\tau)=0$
  if $E^i_{\mathrm{vso}}(\tau)>0$ **then** $E^i_{\mathrm{vso}}(\tau)=0$
end if

Algorithm 4 checks feasibility of Constraints (8), (9), (14), and (15). Because the items in Constraints (8) and (9) (resp., Constraints (14) and (15)) are interrelated and cannot be discussed separately, they are checked in the former (resp., latter) two conditions in Line 2. If violated, Line 3 calls Lines 3–23 of Algorithm 1 to repair the variables at hour τ.

Note that Algorithms 2–3 are adopted for meeting the constraints of charging and discharging the HEE and the EV, and can be executed independently. However, Algorithm 4 is concerned about the energy stored by the HEE and the EV, which is affected by Algorithms 2–3, and hence must be executed after these algorithms.

Algorithm 4 RepairPurchaseSellEnergyBound(hour τ)

1: Compute $E^i_{\mathrm{storage}}(\tau)$ by (10) and $E^i_{\mathrm{vehicle}}(\tau)$ by (17)
2 **if** $E^i_{\mathrm{storage}}(\tau)<0$ or $E^i_{\mathrm{storage}}(\tau)>E^{\max}_{\mathrm{store}}$
  or $E^i_{\mathrm{vehicle}}(\tau)<E^{\mathrm{low}}_{\mathrm{ev}}$ or $E^i_{\mathrm{vehicle}}(\tau)>E^{\max}_{\mathrm{ev}}$ **then**
3: Call Lines 2–23 of Algorithm 1 to repair the variables at hour τ
4: **end if**
5: Compute $E^i_{\mathrm{storage}}(\tau)$ by (10) and $E^i_{\mathrm{vehicle}}(\tau)$ by (17)

V. Experimental Results

A. Experimental environment

Based on specifications of the mainstream facilities in the market (including Tesla Model 3 2017 and Tesla Powerwall 2), parameters for the ES and the EV are set as follows: t^i_{on} = 8, t^i_{off} = 18, $E^{\max}_{\mathrm{store}}$ = 13.5 kWh, $E^{\max}_{\mathrm{ev}}$ = 50 kWh, $E^{\mathrm{low}}_{\mathrm{limit}}$ = 2.5 kWh, $E^{\mathrm{low}}_{\mathrm{ev}}$ = 12.5 kWh, β_{store} = 0.1, β_{ev} = 0, $RATE_{\mathrm{store}}$ = 5 kWh, $RATE_{\mathrm{ev}}$ = 10 kWh, $E^i_{\mathrm{vehicle}}(0)$ = 12.5, and $E^i_{\mathrm{storage}}(0)$ = 0. The amount of the renewable energy generated for each day is referred to the data of residential wind turbines and solar panels in [25], but the number of these energy generating facilities is adjusted for requirement of a household, i.e., this work consider that the end-user has 4 solar panels of 0.25 kW and 1 wind turbine of 1 kW. The amount of the renewable energy collected by these facilities changes with strength of wind and sunlight for each hour (Fig. 3).

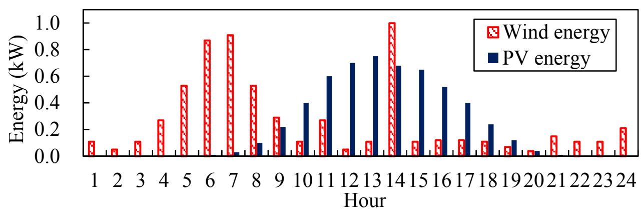

Fig. 3. The renewable energy amount collected by solar panels and a wind turbine for each hour.

The RTP of each hour of one week in the experiment is referred to the data provided by [26], as shown in the solid-line curve in Fig. 4, in which the RTP changes with the energy supply and demand for different hours; the dash-line curves shows the energy price of the energy trading platform, generated by simulation of referring the ratio of the renewable energy amount to the total energy amount in the US and uniform distribution [27].

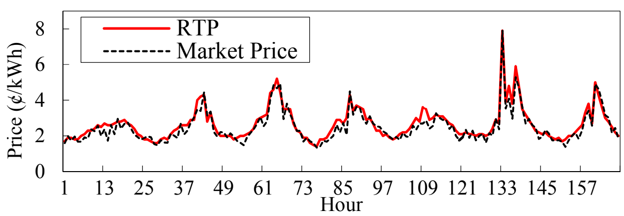

Fig 4. The hourly RTP and market price of one week from Aug. 7 to 13, 2017.

From [28], Fig. 5 shows the grid energy demand of each hour of one day, which is different between a weekday and a weekend. The parameter setting used in the GA is as follows: number of chromosomes is 20; crossover rate is 0.5; mutation rate is 0.01; number of iterations is 10000.

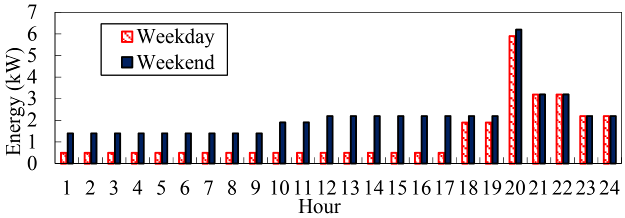

Fig 5. The hourly grid energy demand of the HEE in one day.

B. Experimental Result

With the parameter setting, the energy usage cost of each day of one week using the proposed GA is shown in Fig. 6 and Table 3. From Table 3, the total energy usage cost of the end-user is –353.63¢ for one week, i.e., the end-user earns 353.63¢.

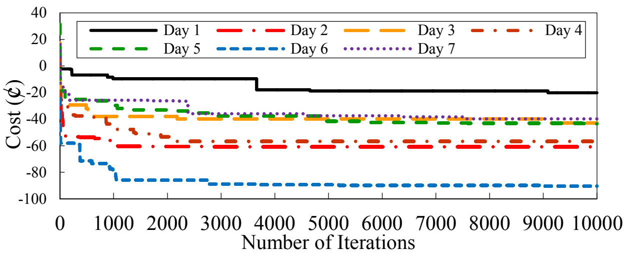

Fig. 6. Results of executing 10000 iterations of the proposed GA for 7 days.

TABLE 3. The energy usage cost of each day of one week.

Day	1	2	3	4	5	6	7
Cost	-20.11	-60.72	-42.79	-56.64	-43.39	-90.27	-39.71

Fig. 7 shows the charge and discharge amounts of the ES and the EV for each hour of one week in the experimental result. From Fig. 7, it is reasonable that most charges occur at the hours of low energy load, and most discharges occur at the hours of peak energy load.

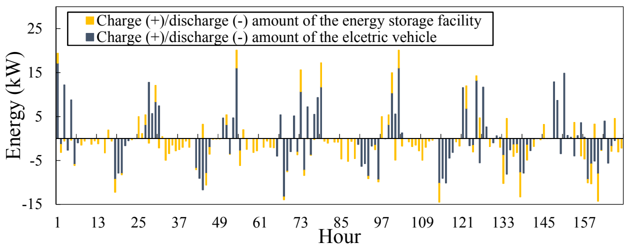

Fig. 7. The charge and discharge amounts of the ES and the EV for each hour of one week.

To the best of our understanding, no previous approaches were proposed for the concerned problem. Therefore, this section compares the proposed GA with two other algorithms that can represent the end-user's reasonable decision. In the first RAND algorithm, the end-user adopts a random feasible solution generated by Algorithm 1. In the second GREEDY algorithm, the end-user charges or discharges the ES/EV greedily at each hour, i.e., minimizing the cost at each hour. Table 4 shows the grid energy waste of one week for three algorithms, in which the proposed GA performs best.

TABLE 4. The grid energy waste of one week for three algorithms.

Algorithm	RAND	GREEDY	Proposed GA
Total cost (¢)	217.95	57.45	-353.63
Ratio of improvement	0%	73.64%	262.26%

Consider a conventional model in which the end-user uses only the energy from the electrical grid of the power company. In contrast, the proposed model additionally includes an ES, an EV, renewable energy generating facilities, and an energy trading platform. Fig. 8 shows the grid energy amount used by the HEE for each hour of one week for the two models. In Fig. 8, the standard deviation of hourly grid energy used by the HEE for our model (0.4117) is less than that for the conventional model (1.2988). Therefore, the supply of grid energy in our model is more stable. From Fig. 8, it is observed that the dependency of the HEE with the grid energy is reduced remarkably. In addition, the power company supplies energy based on the highest energy demand for each day. However, if the highest energy demand is not achieved, the energy supply is wasted. Table 5 shows the grid energy waste of one week for conventional and our models, from which our model decrease the energy waste remarkably.

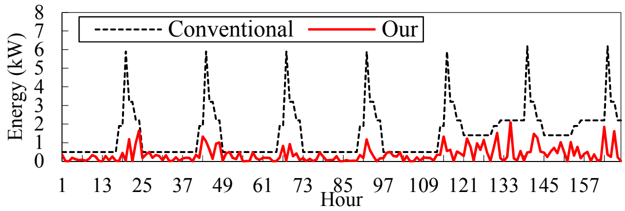

Fig. 8. The grid energy amount used by the HEE for each hour of one week for conventional and our models.

TABLE 5. The grid energy waste of one week for conventional and our models

Model	Conventional	Our
Grid energy waste	794.6	260.8

VI. Conclusion

This work has established an MILP for the problem of making energy-charging decisions of multiple facilities of a single end-user with an EV and an ES in the IoE to minimize the total energy usage cost. A GA is further proposed for this problem. Simulation results on the data for one week show that this model can effectively reduce the grid energy waste of a single end-user. In addition, this model also verifies effectiveness of renewable ESs. In the future, more environmental constraints could be considered, e.g., deployment of outdoor EV charging stations, the subsidy policies on generating green energy, pollution caused by generating energy, and the effect of the optimal decision of each household end-user on the whole electrical grid.

REFERENCES

[1] K. Wang, J. Yu, Y. Yu, Y. Qian, D. Zeng, S. Guo, Y. Xiang, and J. Wu, "A survey on energy Internet: architecture, approach and emerging technologies," *IEEE Syst. J.*, doi: 10.1109/JSYST.2016.2639820.

[2] C.-C. Lin, D.-J. Deng, W.-Y. Liu, and L. Chen, "Peak load shifting in the Internet of energy with energy trading among end-users," *IEEE Access*, vol. 5, pp. 1967–1976, 2017.

[3] J. Kang, R. Yu, X. Huang, S. Maharjan, Y. Zhang, and E. Hossain, "Enabling localized peer-to-peer electricity trading among plug-in hybrid electric vehicles using consortium blockchains," *IEEE Trans. Ind. Informat.*, vol. 13, no. 6, pp. 3154-3164, 2017.

[4] M. G. Ippolito, S. Favuzza, and E. R. Sanseverino, "Economic feasibility of a customer-side energy storage in the Italian electricity market," in *Proc. of EEEIC 2015*, IEEE Press, 2015, pp. 938–943.

[5] B. D. Olaszi and J. Ladanyi, "Comparison of different discharge strategies of grid-connected residential PV systems with energy storage in perspective of optimal battery energy storage system sizing," *Renew. Sustainable Energy Rev.*, vol. 75, pp. 710–718, 2017.

[6] P. Samadi, A. H. Mohsenian-Rad, R. Schober, V. W. Wong, and J. Jatskevich, "Optimal real-time pricing algorithm based on utility maximization for smart grid," in *Proc. of IEEE SmartGridComm 2010*, 2010, pp. 415–420.

[7] C. Chellaswamy and R. Ramesh, "Future renewable energy option for recharging full electric vehicles," *Renew. Sustainable Energy Rev.*, vol. 76, pp. 824–838, 2017.

[8] Y. Zhang, R. Yu, M. Nekovee, Y. Liu, S. Xie, and S. Gjessing, "Cognitive machine-to-machine communications: Visions and potentials for the smart grid," *IEEE Netw.*, vol. 26, no. 3, pp. 6-13, 2012.

[9] X. Fang, S. Misra, G. Xue, and D. Yang, "Smart grid—The new and improved power grid: A survey," *IEEE Commun. Surveys Tuts.*, vol. 14, No. 4, pp. 944–980, 2012.

[10] A. H. Mohsenian-Rad and A. Leon-Garcia, "Optimal residential load control with price prediction in real-time electricity pricing environments," *IEEE Trans. Smart Grid*, vol. 1, no. 2, pp. 120-133, 2010.

[11] A. J. Conejo, J. M. Morales, and L. Baringo, "Real-time demand response model," *IEEE Trans. Smart Grid*, vol. 1, no. 3, pp. 236-242, 2010.

[12] S. Maharjan, Q. Zhu, Y. Zhang, S. Gjessing, and T. Basar, "Dependable demand response management in the smart grid: A Stackelberg game approach," *IEEE Trans. Smart Grid*, vol. 4, no. 1, pp.120-132, 2013.

[13] Y. Wang and D. Infield, "Optimal demand side response to real time price signal using electric vehicles," in *Proc. of RPG 2015*, IEEE Press, 2015.

[14] E. Telaretti and L. Dusonchet, "Battery storage systems for peak load shaving applications: Part 1: Operating strategy and modification of the power diagram," in *Proc. of EEEIC 2016*, IEEE Press, pp. 1-6, 2016.

[15] Y. Ning, X. Li, X. Ma, X. Jia, and D. Hui, "Optimal schedule strategy of battery energy storage systems for peak load shifting based on interior point method," in *Proc. of WCICA 2016*, IEEE Press, 2016, pp. 2285–2288.

[16] A. Rahimi, M. Zarghami, M. Vaziri, and S. Vadhva, "A simple and effective approach for peak load shaving using battery storage systems," in *Proc. of NAPS 2013*, IEEE Press, 2013, pp. 1–5.

[17] P. M. de Quevedo, G. Muñoz-Delgado, and J. Contreras, "Impact of electric vehicles on the expansion planning of distribution systems considering renewable energy, storage and charging stations," *IEEE Trans. Smart Grid*, doi: 10.1109/TSG.2017.2752303.

[18] K. Zhou, S. Yang, and Z. Shao, "Energy internet: the business perspective," *Appl. Energy*, vol. 178, pp. 212-222, 2016.

[19] Z. Zhou, J. Gong, Y. He, and Y. Zhang, "Software defined machine-to-machine communication for smart energy management," *IEEE Commun. Mag.*, vol.55, no.10, pp.52-60, 2017.

[20] Y. Zhang, R. Yu, W. Yao, S. Xie, Y. Xiao, and M. Guizani, "Home M2M networks: Architectures, standards, and QoS improvement," *IEEE Commun. Mag.*, vol. 49, no. 4, pp. 44-52, 2011.

[21] H. Wang and J. Huang, "Incentivizing energy trading for interconnected microgrids," *IEEE Trans. Smart Grid*, doi: 10.1109/TSG.2016.2614988.

[22] P. Yi, T. Zhu, B. Jiang, R. Jin, and B. Wang, "Deploying energy routers in an energy internet based on electric vehicles," *IEEE Trans. Veh. Technol.*, vol. 65, no. 6, pp. 4714-4725, 2016.

[23] S. Chen, N. B. Shroff, and P. Sinha, "Energy trading in the smart grid: From end-user's perspective," in *Proc. of 2013 IEEE Asilomar Conference on Signals, Systems and Computers*, 2013, pp. 327-331.

[24] J. H. Holland, "Adaptation in natural and artificial systems," in *An Introductory Analysis with Application to Biology, Control, and Artificial Intelligence*. Ann Arbor, MI: University of Michigan Press, 1975.

[25] N. Tutkun, F. Ungören, and B. Alpagut, B. "Improved load shifting and valley filling strategies in demand side management in a nano scale off-grid wind-PV system in remote areas," in *Proc. of IEEE ICNSC 2017*, 2017, pp. 13–18.

[26] Commonwealth Edison Company, *Real-time Hourly Prices*, available at: https://hourlypricing.comed.com/live-prices/, accessed in Aug., 2017.

[27] N. Yaagoubi and H. T. Mouftah, "A distributed game theoretic approach to energy trading in the smart grid," in *Proc. of IEEE EPEC 2015*, 2015, pp. 203–208.

[28] N. Tutkun, Ö. Can, and E. S. Şan, "Daily cost minimization for an off-grid renewable microhybrid system installed to a residential home," in *Proc. of ICRERA 2015*, IEEE Press, 2015, pp. 750–754.