Proactive P2P Energy Sharing for a Community via PSO-based Stochastic Optimization

Luyao Zou, and Choong Seon Hong

Department of Computer Science and Engineering, Kyung Hee University, South Korea

Email: {zouluyao, cshong}@khu.ac.kr

Abstract

Peer-to-peer (P2P) energy sharing for a community with the characteristics of consuming energy and generating renewable energy nowadays plays a vital role in the smart city. However, the non-renewable energy is still heavily utilized due to the imbalance problem between energy demand and generation. Hence, we study an energy sharing problem that focuses on minimizing the utilization of non-renewable energy in this paper by considering the charge and discharge process of the battery storage system and electric vehicle storage system. Firstly, we formulate an optimization problem for minimizing the usage of non-renewable energy. Secondly, a PSO-based stochastic optimization approach is proposed to solve this problem by considering P2P energy sharing behaviors and battery/EV storage schedule. Finally, the evaluation results show the presented approach can improve the overall non-renewable energy utilization.

1. Introduction

In recent years, as the development of a smart city, a community is formed by prosumers has become a pivotal way to achieve the minimization problem of the non-renewable energy utilization. However, due to affecting by solar intensity, the solar energy generation becomes uneven, and the energy consumption of smart city users is uncertain [1], which leads the massive utilization of the non-renewable energy. Therefore, a proactive peer-to-peer (P2P) energy sharing method is proposed to solve such a problem.

P2P nowadays has received huge interest in the research of energy such as in [2], a selfish energy sharing mechanism based on non-cooperative game theory was proposed to schedule the battery and to share energy with neighbors. In [3], a two-stage bidding strategy was proposed to solve the problems of lacking of flexibility and unfair on P2P energy trading. Unlike previous studies, we focus on energy sharing to minimize the utilization of the non-renewable energy.

The main contributions are summarized as follows:

- We formulate an energy sharing problem to minimize the utilization of non-renewable energy for the entire community in the smart city. Where we schedule the storage by considering charge and discharge. However, it is difficult to know the optimal value of sharing and charge/discharge.
- To solve such difficulty, we proposed a stochastic optimization approach based on particle swarm optimization (PSO) to obtain the optimal value.
- Finally, we show the proposed method can reduce the usage of non-renewable energy.

The rest of this paper is organized as follows. Section 2 shows the system model and the related formulation. In section 3, the detailed solution is illustrated. The evaluation results are shown in section 4. Finally, section 5 gave the conclusion.

2. System Model and Problem Formulation

This section discusses the system model and the related formulation for a community that is formed by four types of households, shown as Table 1.

Table 1 Four types of Household

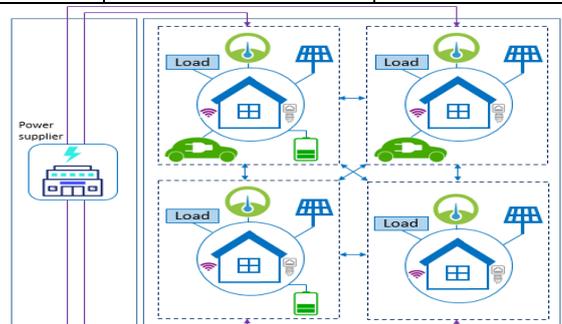| Household Type	Component	
	Battery Storage System	Electrical Vehicle
I	Yes	Yes
II	Yes	No
III	No	Yes
IV	No	No

Fig. 1 System Model

Fig. 1 shows the system model which is composed of the power supplier, multiple households $H = \{1, 2, \ldots, H\}$ with related connections. In this model, the smart meter is utilized to record the energy demand of each household and communicate with the power supplier

and the home energy management system (HEMS). The load $L = \{1,2,...,L\}$ of each household is assumed to connect to HEMS by communication technology. $T = \{1,2,...,T\}$ is the finite time slot in which per time interval $t \in T$ consists of an hour duration [1]. For the energy storage of individual houses, the optimal process is not to charge/discharge simultaneously [4].

For battery storage, without any big errors, the self-discharge can be ignored every month [5]. Therefore, a binary decision variable X can be defined as (1) to indicate the charge and discharge process.

$$X = \begin{cases} 1, & \text{battery } charge, \\ 0, & \text{battery } discharge, \end{cases} \tag{1}$$

Where $X = 1$, if charge of battery occurs, and 0 otherwise. The battery state of the next time slot $P_{h,b}^{s,t+1}$ can be defined as (2) [5].

$$P_{h,b}^{s,t+1} = \begin{cases} X\left(P_{h,b}^{s,t} + \lambda_{inv}\lambda_c P_{h,b}^{c,t}\right), & if \ X = 1 \\ (1-X)\left(P_{h,b}^{s,t} - \frac{P_{h,b}^{d,t}}{\lambda_{inv}\lambda_d}\right), & otherwise, \end{cases} \tag{2}$$

where λ_{inv}, λ_c, λ_d means the inverter, battery charge, and discharge efficiency, respectively, while $P_{h,b}^{s,t}$ is the battery state, $P_{h,b}^{c,t}$ is the charge, $P_{h,b}^{d,t}$ is the discharge at time slot t.

For the electric vehicle storage system. a binary decision variable Y can be defined as (3) to indicate the charge and discharge process.

$$Y = \begin{cases} 1, & \text{EV } charge, \\ 0, & \text{EV } discharge, \end{cases} \tag{3}$$

where $Y = 1$, if EV charge occurs, and 0 otherwise. EV state of the next time slot $P_{h,EV}^{s,t+1}$ is defined as (4) [3].

$$P_{h,EV}^{s,t+1} = P_{h,EV}^{s,t} + Y * \lambda_{EV}^c * P_{h,EV}^{c,t} - (1-Y) * \frac{P_{h,EV}^{d,t}}{\lambda_{EV}^d}. \tag{4}$$

where $P_{h,EV}^{s,t}$ is the EV state, $P_{h,EV}^{c,t}$ is the charge, $P_{h,EV}^{d,t}$ is the discharge at time slot t.

For each household h, the energy consumption of total load $P_h^{l,t}$, energy that can be used $P_h^{u,t}$, and the non-renewable energy $P_h^{n,t}$ are shown as (5), (6)and (7), respectively.

$$P_h^{l,t} = P_h^{d,t} + P_h^{s,t} + P_{h,b}^{c,t} + P_{h,EV}^{c,t}, \tag{5}$$

$$P_h^{u,t} = \lambda_{inv} * P_h^{g,t} + P_h^{r,t} + P_{h,b}^{d,t} + P_{h,EV}^{d,t}, \tag{6}$$

$$P_h^{n,t} = \begin{cases} P_h^{l,t} - P_h^{u,t}, & if \ P_h^{l,t} \geq P_h^{u,t}, \\ 0, & otherwise. \end{cases} \tag{7}$$

where $P_h^{d,t}$ depicts the energy consumption, $P_h^{g,t}$ represents energy generation at time slot t, $P_h^{s,t}$ and $P_h^{r,t}$ indicate energy sharing and receiving, respectively. Sharing can be 0 if demand is greater than the generation of this household. $P_{h,b}^{c,t}$, $P_{h,EV}^{c,t}$, $P_{h,b}^{d,t}$, $P_{h,EV}^{d,t}$ are battery charge, EV charge, battery discharge, and EV

discharge, respectively. When the household does not contain battery or EV, these values are 0.

The objective is to minimize the utilization of the non-renewable energy of the community by the battery or EV charge or discharge scheduling and the energy sharing, the related formulation is shown as follows:

$$\min_{P_h^{s,t}, P_{h,b}^{c,t}, P_{h,b}^{d,t}, P_{h,EV}^{c,t}, P_{h,EV}^{d,t}} \sum_{\forall h \in H} \sum_{\forall t \in T} P_h^{n,t} \tag{8}$$

s.t.
$$0 < \lambda_{inv}, \lambda_d, \lambda_c, \lambda_{EV}^c, \lambda_{EV}^d < 1, \tag{8a}$$

$$\sum_{\forall h \in H} X\left(P_{h,b}^{s,t} + \lambda_{inv}\lambda_c P_{h,b}^{c,t}\right) \leq \sum_{\forall h \in H} b_{max}, \tag{8b}$$

$$\sum_{\forall h \in H}(1 - X)\left(P_{h,b}^{s,t} - \frac{P_{h,b}^{d,t}}{\lambda_{inv}\lambda_d}\right) \geq \sum_{\forall h \in H} b_{min} \tag{8c}$$

$$\sum_{\forall h \in H} SOC_{EV}^{min} \leq \sum_{\forall h \in H} P_{h,EV}^{s,t_{EV}} \leq \sum_{\forall h \in H} SOC_{EV}^{max}, \tag{8d}$$

$$\sum_{h \in H} P_h^{s,t} \leq \lambda_{inv} * \sum_{\forall h \in H} P_h^{g,t} + \lambda_{inv} * \lambda_d * \sum_{\forall h \in H} P_{h,b}^{s,t} + \lambda_{EV}^d * \sum_{\forall h \in H} P_{h,EV}^{s,t}, \tag{8e}$$

$$X, Y \in \{0,1\}, \ t \in T. \tag{8f}$$

In problem (8), constraint (8a) indicates the efficiency values of the inverter, battery charge/discharge, EV charge/discharge are between 0 and 1, while (8b) and (8c) show the limits of the battery. The (8d) shows the limits of the EV storage system. Constraint (8e) indicates the range of sharing. (8f) is the constraint that defines the decision variable X, Y.

3. Solution with PSO-based Stochastic Optimization

Algorithm 1: PSO-based Stochastic Optimization
Input: ω, c_1, c_2, λ_{inv}, λ_c, λ_d, b_{min}, b_{max}, λ_{EV}^c, λ_{EV}^d, SOC_{EV}^{min}, SOC_{EV}^{max}, S, maxIteration, demand_hourly, generation_hourly
Output: P^*
1:    Randomly generate the related four types of households, the initial capacity of battery and EV storage system
2:    Get the difference between aggregate demand and generation, diff
3:    **for** each time slot $t = 1, ..., T$ **do**
4   **Step 1: Initialization**
5:       **for** each particle $k = 1, ..., S$ **do**
6:          **while** True **do**
7:             **if** diff ≥ 0 **then**
8:                Initialize sharing/receiving, battery/EV charge to 0
9:                Randomly obtain discharge of battery satisfy (8c)
10:              **If** not satisfy the energy demand, **then**
11:                  Randomly obtain energy from EV satisfy (8d)
12:             **else**
13:                Initialize discharge of battery and EV to 0
14:                Randomly generate s_r_ran in [0,−diff]
15:                sharing, receiving ← s_r_ran
16:                Randomly generate bc_ran in the remaining extra energy
17:              **if** (8b) **then**
18:                battery_charge ← bc_ran
19:                Update battery capacity, remaining energy (re)
20:                Randomly generate evc_ran within re

```
21:                if (8d) then
22:                    Update EV capacity
23:                end if
24:                break
25:            Initialize personal best: pbest_k
26:        end for
27:        Obtain the global best: gbest
28:    Step 2: Iteration
29:    repeat{
30:        for each particle  k = 1, … , S  do
31:            using eq.(8):  F(p_k)
32:                if F(p_k) < F(pbest_k) then
33:                    pbest_k =  p_k
34:                    if F(pbest_k) < F(gbest) then
35:                        gbest =  pbest_k
36:        end for
37:        for each particle  k = 1, … , S  do
38:            Get velocity  (9)  and position  (10)  s.t (8b,8c,8d,8e)
39:        end for
40:    }utill maxIteration
41:    end for
```

This section shows the proposed method that, shown in Algorithm 1. (9) and (10) is the formula.

$$V_k^{t+1} = \omega V_k^t + c_1 r(pbest_k^t - p_k^t) + c_2 r(gbest_k^t - p_k^t). \quad (9)$$

$$P_k^{t+1} = p_k^t + V_k^{t+1}. \quad (10)$$

where P is the position and V is velocity, ω represents the momentum, r is the uniform random value. c_1 and c_2 are the constants that determine the effects of the personal best and the global best, respectively.

The fitness function $F()$ determines the performance of PSO. Here, the objective (11) is defined as the fitness function and the observation per time slot is depicted by $P_t = \{P_t^s, P_t^r, P_b^{c,t}, P_b^{d,t}, P_{EV}^{c,t}, P_{EV}^{d,t}\}$, where P_t^s, P_t^r, $P_b^{c,t}$, $P_b^{d,t}$, $P_{EV}^{c,t}$, $P_{EV}^{d,t}$ are the total energy sharing, total receiving, total battery charge, total battery discharge, total EV charge, total EV discharge of the community at time slot t, respectively.

4. Performance Evaluation

In this paper, we use the solar panel dataset [6] for generation and the residential dataset [7] for energy consumption. The related parameters are $\lambda_{inv} = 0.96$, $\lambda_c = 0.958$, $\lambda_d = 0.958$, $\lambda_{EV}^c = 0.95$, $\lambda_{EV}^d = 0.95$ $b_{min} = 0\ KWh$, $b_{max} = 13.5\ KWh$[5], $SOC_{EV}^{min} = 4.8\ KWh$, $SOC_{EV}^{max} = 16KWh$.[1][3]

Fig. 2 shows the usage of non-renewable energy before sharing and minimum usage after sharing of case 1 that has 3 houses with both battery and EV, 2 houses only with the battery, 4 houses only with EV, and 8 houses without any storage. Similarly, Fig. 3 shows the result of case 2 that has 7, 2, 2, and 6 houses of type I, type II, type III, and type IV, respectively. It can

be seen that the usage of non-renewable energy can be minimized and when increasing the type I house, the non-renewable energy utilization can be reduced more.
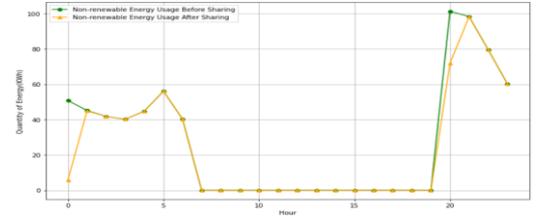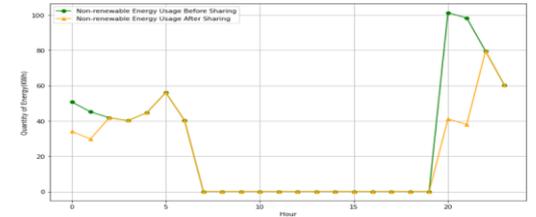

Fig. 2 Non-renewable Energy Utilization of Case 1

Fig. 3 Non-renewable Energy Utilization of Case 2

5. Conclusion

In this paper, a PSO-based stochastic method is proposed to minimize the utilization of the non-renewable energy. The evaluation results show the proposed method can gain an effect on minimizing the utilization of the non-renewable energy.

References

[1] L. Zou, Md. Shirajum Munir, Kitae Kim, and Choong Seon Hong, "Day-ahead Energy Sharing Schedule for the P2P Prosumer Community Using LSTM and Swarm Intelligence", 2020 International Conference on Information Networking (ICOIN), 2020.

[2] M. Pilz and L. Al-Fagih, "Selfish Energy Sharing in Prosumer Communities: A Demand-Side Management Concept," arXiv, 2019.

[3] Z. Zhang, H. Tang, Q. Huang and W. Lee, "Two-Stages Bidding Strategies for Residential Microgrids Based Peer-to-Peer Energy Trading," 2019 IEEE/IAS 55th Industrial and Commercial Power Systems Technical Conference (I&CPS), Calgary, AB, Canada, 2019.

[4] S. Cui, Y. Wang, Y. Shi, and J. Xiao, "An Efficient Peer-to-Peer Energy Sharing Framework for Numerous Community Prosumers", IEEE Transactions on Industrial Informatics, 2019.

[5] L. Zou, and C. S. Hong, "Intelligent Energy Scheduling with Considering Battery Storage System Using Particle Swarm Optimization", KSC 2019, pp. 320-322, 2019 (in Korea).

[6] Online: "Solar panel dataset", UMassTraceRepository: http://traces.cs.umass.edu/index.php/Smart/Smart.

[7] Online: "USA_LA_*," RESIDENTIAL_LOAD_DATA_E_PLUS*, https://openei.org/datasets/files/961/pub/.