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Performance Evaluation of Peer-to-Peer Energy Sharing Models

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Abstract

With the increasing installation of distributed generation at the demand side, an increasing number of consumers become prosumers, and many peer-to-peer (P2P) energy sharing models have been proposed to reduce the energy bill of the prosumers through stimulating energy sharing and demand response. In this paper, a three-stage evaluation methodology is proposed to assess the economic performance of P2P energy sharing models. First of all, joint and individual optimization are established to identify the value contained in the energy sharing region. The overall energy bill of the prosumer population is then estimated through an agent-based modelling with reinforcement learning for each prosumer. Finally, a performance index is defined to quantify the economic performance of P2P energy sharing models. Simulation results verify the effectiveness of the proposed evaluation methodology, and compare three existing P2P energy sharing models in a variety of electricity pricing environments.

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Keywords: Energy sharing; Peer to peer; Prosumers; Performance evaluation; Agent-based modelling; Reinforcement learning

1. Introduction

With the increasing installation of distributed generation at the demand side, more and more consumers become prosumers that can both generate and consume energy. The high penetration of intermittent renewable energy may cause severe problems to power systems. Therefore, in order to facilitate the self-consumption of local generation, the export price at which the prosumers sell electricity to the utility grid is usually designed to be lower than the retail price at which they buy electricity [1]. This fact provides the fundamental motivation for prosumers to share surplus

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energy with each other rather than to feed it back to the utility grid. The decreasing tariff rate of the feed-in tariff in many countries makes the incentive even stronger.

Motivated by this practical need, a rapidly growing number of projects have been started by utilities, manufacturers and high-tech start-ups [2]. A number of projects, including Piclo in the UK, Vandebron in the Netherland, SonnenCommunity in Germany and Yeloha and Mosaic in the US, established national or regional online platforms that support peer-to-peer (P2P) energy sharing between prosumers. Some projects, such as PeerEnergyCloud and Smart Watts in Germany, focused on the information and communication technologies supporting the energy sharing. There are also some projects, such as TransActive Grid in the US, which developed decentralized energy sharing platforms based on blockchain technology.

Energy sharing models, which specify how the prosumers exchange and trade energy with each other, are the core of the energy sharing projects. Many studies have been made in this field, which can be divided into three categories: 1) energy sharing conducted by one centralized authority; 2) energy sharing achieved by the interaction between an operator (price maker) and a group of prosumers (price takers); 3) energy sharing achieved by the interaction of a group of prosumers, i.e. the P2P energy sharing. This paper focuses on P2P energy sharing, and some models have been devised, including the bill sharing (BS) model, the mid-market rate (MMR) model [3] and the supply and demand ratio (SDR) model [1].

With these developed P2P energy sharing models, there is still a lack of general methodology to evaluate and compare their performance. First of all, the existing studies compared the cases with and without certain P2P energy sharing models to justify the resulting energy bill savings, but failed to reveal to what extent the P2P energy sharing models have tapped the potential value contained in the P2P energy sharing. Secondly, the convergence of the prosumer decisions under some existing P2P energy sharing models rely on specific appliance and behavior models, resulting in that it is very difficult to compare different P2P energy sharing models in a unified case. Last but not least, there is no established evaluation index to quantify the performance of P2P energy sharing models.

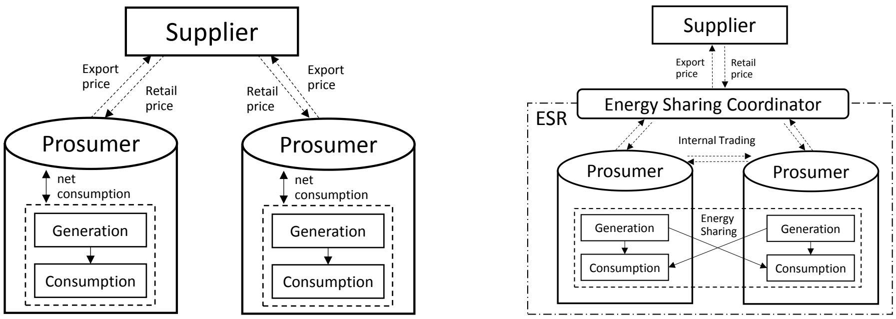
To fill the above research gaps, a general evaluation framework is proposed in this paper to assess the performance of P2P energy sharing models. The framework includes three stages, which correspond to the three challenges described above. First of all, the potential value contained in the P2P energy sharing is identified through joint and individual optimization of prosumers. Secondly, an agent-based computational modelling with a reinforcement learning algorithm is used to obtain the convergence state of prosumer behaviors at which the overall energy bill is estimated. Finally, a performance index is defined based on the value identified and bill estimated to reflect the economical performance of P2P energy sharing models.

2. Peer-to-peer energy sharing paradigm and models

Energy sharing is a new business model at the demand side of power systems, which brings greater economic benefits for prosumers. In the conventional paradigm, suppliers purchase the energy from large generators in the wholesale market and then sell it to end users in the retail market. As shown in Fig. 1(a), traditionally, prosumers trade with suppliers separately, buying/selling energy from/to suppliers at the retail/export price according to the net consumption.

In the new energy sharing paradigm, prosumers exchange and trade energy with each other directly in an energy sharing region (ESR), as shown in Fig. 1(b). An energy sharing coordinator manages the internal energy sharing, and acts as an agent of the prosumers to trade with the external suppliers if there is any energy surplus/deficit in the ESR. With the internal energy sharing, for the whole group of the prosumers in the ESR, a smaller amount of energy will be imported from the suppliers, resulting in lower electricity cost. However, at the same, the energy exported to the suppliers will reduce by the same amount, resulting in lower income as well. In spite of this, due to the fact that the export price is lower than the retail price, the overall energy cost of the prosumers will still be reduced through energy sharing.

Peer-to-peer energy sharing models specify at what prices the prosumers trade energy with each other (i.e. the internal buying/selling price) and how to calculate the energy bill for the prosumers. Different rules adopted in the ESR provide different incentives for flexible demands and distribute the interests obtained from energy sharing in a different way. Therefore, the design of P2P energy sharing models is of great importance in tapping the maximum value in the ESR and distributing the interests fairly.



(a) Conventional paradigm (b) P2P energy sharing paradigm

Fig. 1. Conventional and P2P energy sharing paradigms

3. Evaluation framework and methods

In this section, an evaluation framework is established to assess the performance of P2P energy sharing models. The fundamental objective is to quantify to what extent the model has tapped the potential value contained in the ESR. The framework is composed of three stages: 1) value identification, 2) bill estimation, and 3) performance index.

3.1. Value Identification

The value contained in the ESR needs to be identified before evaluating any specific P2P energy sharing models. First of all, the maximum value contained in the ESR is calculated by jointly scheduling the loads and generation units of all the prosumers to maximize the income of the whole ESR:

$$
\begin{aligned}
& value_{\max} = \max\left\{-\sum_{t\in T} p_t^{\text{external}} \left| \sum_{n\in N}\sum_{m\in M}\left(x_{n,m,t}+P_{n,t}^{\text{must-run}}\right)-\sum_{n\in N} G_{n,t}\right| \Delta t\right\} \\
& s.t.\quad \boldsymbol{f}(\boldsymbol{x}) \geq \mathbf{0} \qquad \boldsymbol{g}(\boldsymbol{x}) = \mathbf{0} \\
& \qquad p_t^{\text{external}} = \begin{cases} p_t^{\text{retail}} & \sum_{n\in N}\sum_{m\in M}\left(x_{n,m,t}+P_{n,t}^{\text{must-run}}\right) \geq \sum_{n\in N} G_{n,t} \\ p_t^{\text{export}} & \sum_{n\in N}\sum_{m\in M}\left(x_{n,m,t}+P_{n,t}^{\text{must-run}}\right) < \sum_{n\in N} G_{n,t} \end{cases}
\end{aligned}
\tag{1}
$$

where p is electricity price; x is the power of flexible load; $P^{\text{must-run}}$ is the total power of uncontrollable loads; G is the power output of local generation; Δt is the length of a time step. For the superscripts, "retail" and "export" are the retail and export price offered by the suppliers. For the subscripts, t, n and m are the index of time step, prosumer and flexible load; T, N and M are the set of all the time steps, prosumers and flexible loads of a prosumer. $\boldsymbol{f}(\cdot)$ and $\boldsymbol{g}(\cdot)$ are the inequality and equality constraints that represent device limits and prosumer requirements.

The lower bound of the value contained in the ESR is identified as well to give the baseline scenario in which each prosumer optimizes its own load schedule without considering any energy sharing with other prosumers, representing that there is not any energy sharing model adopted to stimulate energy sharing and demand response in the ESR. The specific formula are as follows.

$$
\begin{aligned}
& value_{\min} = -\sum_{t\in T} p_t^{\text{external}} \left| \sum_{n\in N}\sum_{m\in M}\left(x_{n,m,t}+P_{n,t}^{\text{must-run}}\right)-\sum_{n\in N} G_{n,t}\right| \Delta t \\
& where\quad p_t^{\text{external}} = \begin{cases} p_t^{\text{retail}} & \sum_{n\in N}\sum_{m\in M}\left(x_{n,m,t}+P_{n,t}^{\text{must-run}}\right) \geq \sum_{n\in N} G_{n,t} \\ p_t^{\text{export}} & \sum_{n\in N}\sum_{m\in M}\left(x_{n,m,t}+P_{n,t}^{\text{must-run}}\right) < \sum_{n\in N} G_{n,t} \end{cases} \\
& \qquad x_{n,m,t} = \arg\min \sum_{t\in T} p_t^{\text{external}} \left| \sum_{m\in M}\left(x_{n,m,t}+P_{n,t}^{\text{must-run}}\right)-G_{n,t}\right| \Delta t \quad \forall n\in N \\
& \qquad\quad s.t.\quad \boldsymbol{f}_n(\boldsymbol{x}_n) \geq \mathbf{0} \qquad \boldsymbol{g}_n(\boldsymbol{x}_n) = \mathbf{0} \\
& \qquad\qquad p_t^{\text{external}} = \begin{cases} p_t^{\text{retail}} & \sum_{m\in M}\left(x_{n,m,t}+P_{n,t}^{\text{must-run}}\right) \geq G_{n,t} \\ p_t^{\text{export}} & \sum_{m\in M}\left(x_{n,m,t}+P_{n,t}^{\text{must-run}}\right) < G_{n,t} \end{cases}
\end{aligned}
\tag{2}
$$

With Equation (1) and (2), the upper and lower bound of the value contained in the ESR are identified, which can be used to assess at what level a P2P energy sharing model taps the value in the region.

3.2. Bill Estimation

Before evaluating a P2P energy sharing model, the overall energy bill needs to be estimated. There are three categories of methods for estimating the bill under certain energy sharing model: 1) a centralized manner in form of equilibrium problem with equilibrium constraints (EPEC), 2) an iterative fixed-point "diagonalization" algorithm, and 3) an agent-based computational method. Considering that we are looking at a general evaluation framework and that many of the P2P energy sharing models may not satisfy the conditions required by the former two methods, the agent-based computational method is used. Specifically, a modified diagonalization algorithm with reinforcement learning for each prosumer is established inspired by Evaggelos et al [4], as shown in Fig. 2.

```
Initialize a starting point to each prosumer: p^internal(0) = [p^buy(0) p^sell(0)] = [p_1^buy(0),... p_t^buy(0),... p_|T|^buy(0) p_1^sell(0),... p_t^sell(0),... p_|T|^sell(0)]
for k = 1 to |K|
    for n = 1 to |N|
        Each prosumer estimates the internal prices of the ESR through the proposed reinforcement learning ( p_n^esti-inter(k) )
        Each prosumer optimizes its load schedule according to p_n^esti-inter(k)
    end for
    Update the internal prices p^internal(k) according to the P2P energy sharing model
    if max | p_n^esti-inter(k) - p_n^esti-inter(k-1) | <= ε   ∀n ∈ N
        The iteration converges. End the for loop.
    end if
end for
```

Fig. 2. Modified diagonalization algorithm with reinforcement learning.

In Fig. 2, k is the iteration counter and $\boldsymbol{K}$ is the set of all the iterations. The superscript "internal" is the internal electricity prices in the ESR, including buying and selling price represented by the superscripts "buy" and "sell". The superscript "esti-inter" represents the internal prices estimated by the prosumer. The algorithm is a flexible framework in which each prosumer can use different device models and objectives when optimizing its load schedule and there is no specific requirement for the form of the P2P energy sharing model used. Moreover, theoretically any learning techniques can be used to simulate the decision process of the prosumers, although in this study the following reinforcement learning is used:

$$p_{n,t}^{\text{esti-inter}(k)} = 0.5(1-\gamma)p_t^{\text{inter}(k-1)} + \gamma \sum_{i=k-W}^{k-1} \left(\omega_{n,i} p_t^{\text{inter}(i)}\right) + 0.5(1-\gamma)\left[p_t^{\text{export}} + \mu\left(p_t^{\text{retail}} - p_t^{\text{export}}\right)\right]$$
$$\text{where} \quad \omega_{n,i} = \frac{Actual\_Income_{n,i}}{\sum_{i=k-W}^{k-1} Actual\_Income_{n,i}} \qquad \forall n \in \boldsymbol{N}, t \in \boldsymbol{T}, k \in \boldsymbol{K} \tag{3}$$

where γ is the learning rate, μ is a random number, ω are the weights, and γ , μ and ω take values from [0, 1]. *Actual_Income* represents the total income (the opposite number of the total electricity cost) of a prosumer. From Equation (3), it can be seen that the estimation of the internal prices is the weighted sum of three parts: 1) the internal prices of the last iteration, 2) the weighted sum of the internal prices of the past iterations, and 3) random numbers.

With the algorithm shown in Fig. 2, the convergence state of the prosumers' behaviors the ESR can be obtained, so that the overall energy bill of the ESR can be calculated.

3.3. Performance Index

Based on the value identified in Section 3.1 and the overall energy bill calculated in Section 3.2, the following index is defined to reflect the economic performance of P2P energy sharing models:

$$PI = \frac{income_{\mathrm{ESR}} - value_{\min}}{value_{\max} - value_{\min}} \quad (4)$$

where PI represents performance index; $value_{\max}$ and $value_{\min}$ are the maximum and minimum value contained in the ESR; $income_{\mathrm{ESR}}$ is the overall income of the ESR calculated based on the convergence state obtained in Section 3.2. The performance index takes value from [0, 1]. The higher the index is, the better the P2P energy sharing model is in terms of bringing more economic benefits to the prosumer population. If the index equals to 1, it demonstrates that the model has tapped all the value contained in the ESR, and no better models can be designed in the scenarios studied.

4. Case study

4.1. Case Design

Three existing P2P energy sharing models (BS, MMR and SDR) are evaluated in a community microgrid composed of 10 residential prosumers. The community microgrid is connected to the utility grid, and the prosumers can buy/sell electricity from/to suppliers. Five prosumers are equipped with photovoltaic (PV) panels on the roof, and the other five prosumers do not own local generation (strictly speaking they are consumers rather than prosumers, but they can be treated as prosumers with zero local generation without losing any generality and they can contribute to the energy sharing through demand response). All the prosumers have uncontrollable appliances as well as flexible appliances.

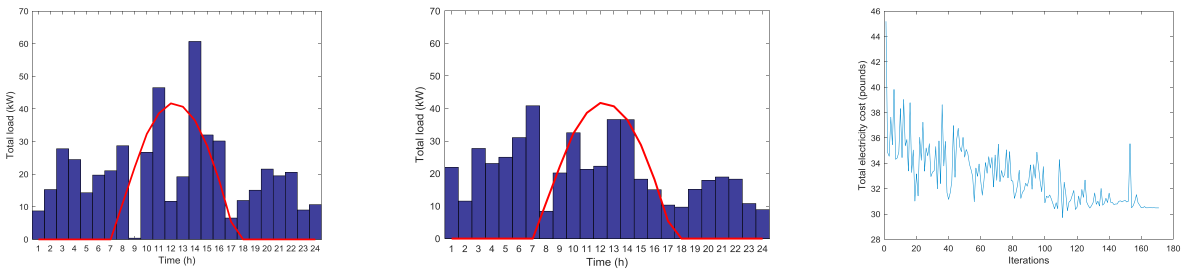
A typical summer day is chosen to evaluate the models. The solar radiation, the demand curve of uncontrollable loads and the parameters and demands of flexible loads all refer to the case design in Reference [5]. All the prosumers are assumed to perform day-ahead load scheduling, and the length of the time steps is 1 hour.

4.2. Base Case

A base case is assessed to demonstrate the procedure and effectiveness of the proposed evaluation methodology. A typical Economy 7 tariff in the UK is taken as the retail price (with off-peak rate 7.88 pence/kWh from 0:00 to 7:00 and standard rate 18.30 pence/kWh from 7:00 to 24:00), and the current export price in the UK feed-in tariff scheme is taken as the export price (5.03 pence/kWh). The SDR model is evaluated using the proposed methodology. The results of each stage of the evaluation procedure is presented as follows.

First of all, the upper and lower limit of the value contained in the ESR (the community microgrid consisting of 10 prosumers) are identified by running the joint and individual optimization as shown in Equation (1) and (2). After optimization, it is calculated that the upper limit of the value is £-28.26 and the lower limit of the value is £-37.52 (the negative numbers mean that the prosumers pay electricity cost rather than have income through selling electricity).

Afterwards, the overall energy bill of the ESR under the SDR model is calculated using the modified diagonalization algorithm with reinforcement learning. Comparing the total load curves of the early and final iteration as shown in Fig. 3(a) and Fig. 3(b), it can be seen that the SDR model is able to stimulate prosumers to share their surplus solar energy, and the overall energy bill of the ESR finally converges to a low level, as shown in Fig. 3(c).



(a) Load and Generation curves at 5th iteration (b) Load and Generation curves at final iteration (c) The convergence process

Fig. 3. Simulation results in the "bill estimation" stage (total load: blue bar; total generation: red line)

Finally, with the value identified and energy bill estimated, the value of the performance index can be calculated as follows: PI = [-30.48-(-37.52)]/[(-28.26)-(-37.52)] = 0.76. This demonstrates that the SDR is able to tap 76% value contained in the ESR in this case.

4.3. Comparison of different P2P energy sharing models and the sensitivity of electricity prices

Three existing P2P energy sharing models, i.e. the BS, MMR and SDR model, are evaluated using the proposed methodology given a variety of electricity pricing environments (including time-of-use and flat tariff for retail prices and three levels of export prices). The performance index values in different scenarios are presented in Table 1. Three observations can be made: 1) The values of the BS model are very low in every scenario, showing that it almost cannot stimulate energy sharing and demand response. This result is consistent with the design of the BS model, which just averages the energy bill of all the prosumers and thus includes very weak incentive for demand response; 2) The MMR and SDR model performs perfect with the flat rate because they both include internal dynamic pricing mechanisms to stimulate energy sharing and demand response; 3) Both the MMR and SDR model perform worse with Economy 7 compared to flat rate. The reason may be that a more complex market environment makes the prosumers more difficult to converge to the global optimum. The simulation results show that generally the SDR model performs better than the MMR model, and the performance of the MMR model enhances with the export price under Economy 7.

Table 1. Evaluation results of three existing P2P energy sharing models under different electricity pricing environments.

Retail Price (pence/kWh)	Export Price (pence/kWh)	Performance Index		
		Bill Sharing (BS)	Mid-Market Rate (MMR)	Supply and demand ration (SDR)
Economy 7 7.88 (0:00-7:00) 18.30 (7:00-24:00)	5.03	0.03	0.69	0.72
	2.51	0.03	0.55	0.78
	0.00	0.06	0.45	0.72
Flat Rate 14.57	5.03	0.02	1.00	1.00
	2.51	0.07	1.00	1.00
	0.00	0.14	1.00	1.00

5. Conclusions

A general evaluation methodology is established in this paper to assess the economic performance of P2P energy sharing models. The proposed methodology is able to identify the potential value, estimate the energy bill and finally give the performance index value of P2P energy sharing models. Simulation results verify the effectiveness of the proposed methodology, and conclude that in the test cases the economic performance of the SDR model is slightly better than the MMR model and both of SDR and MMR model are significantly better than the BS model.

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