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A distributed power sharing framework among households in microgrids: a repeated game approach

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Abstract In microgrids, the integration of distributed energy resources (DERs) in the residential sector can improve power reliability, and potentially reduce power demands and carbon emissions. Improving the utilization of renewable energy in households is a critical challenge for DERs. In this regard, renewable power sharing is one of the possible solutions to tackle this problem. Even though this solution has attracted significant attention recently, most of the proposed power sharing frameworks focus more on centralized schemes. In contrast, in this paper, the performance of a proposed distributed power sharing framework is investigated. The problem is formulated as a repeated game between households in a microgrid. In this game, each household decides to cooperate and borrow/lend some amount of renewable power from/to a neighboring household, or to defect and purchase the entire demands from the main grid based on a payoff function. The Nash equilibrium of this game is characterized and the effect of the strategies taken by the households on the system is analyzed. We

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conduct an extensive evaluation using real demand data from 12 households of different sizes and power consumption profiles in Stockholm. Numerical results indicate that cooperation is beneficial from both an economical and environmental perspective and that households can achieve cost savings up to 20 %.

Keywords Microgrids · Game theory · Demand side management · Distributed energy resources · Electricity cost minimization problem · Carbon emission reduction strategies

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1 Introduction

Increased energy demand, the devastating risks of climate change, and ambitious emissions reduction targets have lead to significant changes in the approach of how to produce, distribute, and consume electricity [1,2]. However, the increased energy demand, along with the decreasing fossil energy sources, is usually accompanied by a significant increase in the electricity prices. In 2013, for instance, the average EU residential prices were 0.20 euro/kWh, a 43 % increase from the average 2006 price of 0.14 euro/kWh [3].

Smart grids symbolize the transition from conventional electricity grids, where electricity flows one-way from generators to consumers, to interconnected and flexible grids that ensure a bidirectional flow of electricity and information between power plants and appliances, and all points in between. Smart grids are intelligently integrated operational and technological systems for optimizing power generation, distribution, and consumption across a city, and may be considered as a key component of sustainable smart cities, opening up for a broad spectra of new technologies and business models to increase energy efficiency and reduce climate impact [4,5].

Demand-side management (DSM), a key integral part of the concept of smart grids, refers to management strategies that aim to increase the involvement of end-consumers in the planning and implementation of innovative energy efficiency measures and solutions [6].

Further developing the architecture of smart grids, integration of distributed energy resources (DERs) solutions can bring further reduction in power demands. Many households and residential buildings are beginning to adopt small-scale on-site renewable energy production sources, such as solar panels. However, as renewable energy is intermittent due to its nature, they keep connected to the main grid to secure their power demand during times of the day when renewable energy generation is impossible due to external whether conditions [7]. Connecting a group of households with DERs forms what is called a “microgrid” [7] which possibly has the capability to control energy transfer between households and to help in improving energy efficiency. On the other hand, households may have different power demand profiles due to various factors such as occupants social grade and employment status, as well as the number and age of occupants. Besides, the time when renewable energy is harvested and the time of households' power consumption do not necessarily overlap. As an effect, a mismatch occurs between the local generation of renewable energy and local power consumption in some households, which reduces the utilization of local DERs.

Using energy storage [7] and injecting the surplus renewable energy into the grid [8] are among the possible solutions that increase the benefit of adopting on-site renewables. However, equipping each household with an on-site energy storage unit may be economically unaffordable due to the high cost of batteries which are required to buffer sufficient renewable energy for an average household daily power consumption [9], such as the recently announced Tesla Powerwall battery [10]. Besides, batteries with long cycle life have a big physical size that makes them difficult to be located inside households (e.g., Vanadium Redox-flow batteries [11,12]). In addition, reinjecting power from unpredictable DERs, such as solar energy, into the main grid at a large scale (i.e., exceeding a certain limit) may cause grid instabilities. For instance, there are strict laws in the US that limit the total number of participating households that can inject renewable energy into the grid [8].

Considering the fact that households' electricity consumption patterns do not necessarily overlap, an alternative possible solution to maximize the potential of DERs is to allow households to share their renewable energy among each other in a cooperative fashion. Recently, power sharing mechanisms in smart grids and microgrids have received significant attention [13–16]. The authors in [13] introduce a centralized and shared energy storage system for microdgrids that allows households to improve the utilization of their local DER. In [14], another shared energy storage framework is proposed for the cost savings trade-off problem among multiple users in a demand response system using a Markovian model. The work presented in [15] uses a greedy matching algorithm to determine which households should share energy in order to reduce energy losses. The authors assume that all households are always willing to share energy with each other. A peer-to-peer energy sharing framework between multiple neighboring microgrids in a distribution network is proposed in [16].

While interesting, most of this existing body of literature [13–15] has primarily focused on centralized power sharing architectures. Moreover, the environmental potential, such as CO_2 emissions reduction, has not been paid attention. However, it is interesting to define a distributed approach that can give households full control and ability to adapt to the changes within the system, and investigate the benefit of power sharing in this case.

In this paper, we assess the economical and environmental potential of a proposed distributed power sharing framework for microgrids, where households can cooperate to reduce their demands from the main grid by exchanging some amount of renewable energy among each other. The interaction between rational households is modeled via a repeated power sharing game. Game theory has been used recently in a remarkable amount of research in this area since it provides efficient analytical tools to model interactions among entities with conflicting interests in a distributed manner [17]. In contrast to one-shot games, players in repeated games interact with each other for multiple rounds, and in each round they play the same game. In such situations, players have the opportunity to adapt to their opponents' behavior (i.e., learn) and try to become more successful, which is very useful in the proposed distributed power sharing framework. To the best of our knowledge, this work is among the first attempts that investigates the usability of game theory formulations to design a decentralized power sharing framework between households in microgrids.

The discussions and analysis in this paper extend the preliminary results in our earlier conference paper [18] in various directions. First of all, the game-theoretic model in this paper is more elaborate and the analysis includes new discussions on strategy-proof properties. Secondly, the focus of this paper is not limited to cost minimization analysis only, but we also present the environmental potential, expressed as CO_2 emissions reduction per kWh of electricity demands, of using the proposed framework. Finally, the simulation results presented in this paper are extended and based on real hourly pricing tariffs and real solar power and demand measurement data for households of different sizes and consumption profiles.

The paper is structured as follows. The system model is illustrated in Sect. 2. The proposed repeated game model is described and analyzed in Sect. 3. In Sect. 4, the distributed power sharing algorithm is presented. Numerical results are discussed in Sect. 5. Finally, we conclude the paper and give pointers for possible future directions in Sect. 6.

2 System model

In this study we consider a generic microgrid which consists of a set of households $\mathcal{N} = \{1, \ldots, N\}$, where $N = |\mathcal{N}|$, with a small-scale on-site DER (e.g., a solar PV panel). Households are connected to each other and to the main grid via AC power lines. Further, it is assumed that households' power demands may be variable both in quantity and time and that they can approximately predetermine their future demands. Time is divided in periods (e.g., days) and each time period is divided in slots (e.g., hours), which represent the time instants at which a certain event or an interaction may occur in the system (i.e., borrowing/lending a certain amount of power).

In fact, households' electricity consumption patterns do not necessarily overlap with each other which can be exploited to reduce the need of purchasing electricity from the main grid. This can be achieved by allowing households to share their renewable energy in a cooperative fashion. At a certain time slot each household can be a power supplier and share some amount of its harvested renewable power, and/or a demander which may request some amount of renewable power from another household.

Further, the applied model assumes that each household is equipped with a smart energy meter, which monitors and controls energy harvesting and power consumption intelligently. Smart meters are also responsible of data communications between households themselves and between households and the main grid. They exchange information about households' demands, available renewable energy, and pricing tariffs at each time slot. The proposed system architecture is illustrated in Fig. 1.

Let $\mathcal{H} = \{1, \ldots, H\}$ denote the set of time slots. A power action of a household $i \in \mathcal{N}$ depends on a time slot $h \in \mathcal{H}$. At every time slot h, each household i has two values: (1) an amount of renewable power S_i^h, generated by its on-site solar panel, and (2) an amount of power demand D_i^h, where $S_i^h, D_i^h \in \mathbb{R}$. From these values a household can determine at every h if an additional power demand is needed or if it

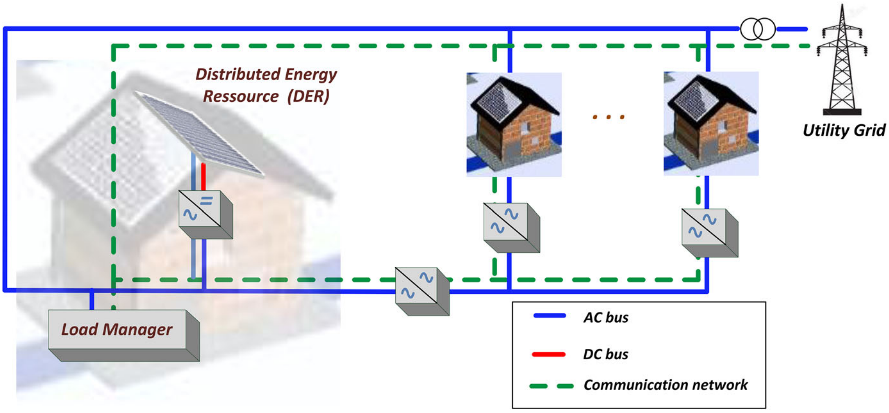

Fig. 1 The proposed microgrid architecture

has a surplus amount of renewable power. We assume that households satisfy their demands first from their own DER. After that, if an amount of renewable power remains or if an additional demand is still needed, they can cooperate and borrow/lend each other. This is achieved by subtracting the renewable power value from the demand value as follows:

$$P_i^h = D_i^h - S_i^h \tag{1}$$

After a series of time slots, each household i will have a power vector P_i that indicates the additional demands as well as the surplus renewable power at each time slot h. This power vector is defined as $P_i = [P_i^1, P_i^2, \ldots, P_i^H]$, where $P_i^h \in \mathbb{R}$.

Negative values of P_i indicate the required additional demands at the corresponding time slots, while positive ones represent the surplus renewable power that could be shared with other households. Then, each household will have two vectors that can exchange with other households: (1) $\hat{D}_i = [\hat{D}_i^1, \hat{D}_i^2, \ldots, \hat{D}_i^H]$ which contains the additional demands at each time slot $h \in \mathcal{H}$, and (2) $\hat{S}_i = [\hat{S}_i^1, \hat{S}_i^2, \ldots, \hat{S}_i^H]$ which contains the surplus renewable power at each time slot $h \in \mathcal{H}$, where $\hat{S}_i^h, \hat{D}_i^h \in \mathbb{R}$. Each time slot can represent different timing horizons (e.g., an hour), where the relationship between P_i vector and $\hat{S}_i$ and $\hat{D}_i$ vectors can be described as follows:

$$P_i = \hat{D}_i + \hat{S}_i \tag{2}$$

3 Repeated power sharing game

3.1 Game formulation

The power exchange among households in the microgrid community is formulated using a discounted repeated game, proposed by [19]. Consider a finite normal form stage game denoted by tuple $\mathcal{G} = (\mathcal{N}, \{\mathcal{S}_i\}_{i\in\mathcal{N}}, \{u_i\}_{i\in\mathcal{N}})$, where $\mathcal{N}$ is the set of players in the game composed of all households in a microgrid community, $\mathcal{S}_i$ is the strategy space available for player $i \in \mathcal{N}$, and u_i is the utility function for player i.

Households are playing the same stage game $\mathcal{G}$ repeatedly over time. In each stage, each household has the following available actions:

- Cooperate (C): Household i cooperates and shares an amount of its renewable power with another household in the microgrid in order to increase its payoff.
- Defect (D): Household i stops playing and sharing its renewable power with its opponent if the opponent defects or if a certain benefit is not achieved.

The utility function u_i is the function used to calculate the payoff of household i from playing the game, capturing the monetary benefit earned by sharing energy with other players. The household's power cost for additional demands, that has to be purchased from the grid and its residual renewable energy can be used to determine the benefit (i.e., cost savings and accompanied emissions reduction) earned by sharing power, and it is considered to be the main factors of the utility function in this game. The utility function of household i is defined as:

$$u_i(s_i, s_{-i}) = \sum_{h \in \mathcal{H}} c_i^h \hat{D}_i^h - \alpha_i^h \hat{S}_i^h \tag{3}$$

where c_i^h is the cost of purchasing 1 kWh from the grid at time slot $h \in \mathcal{H}$. In case of cooperation, where a household receives a certain amount of renewable power from neighboring households, its additional demand's cost is reduced (i.e., an implicit benefit is achieved). $\sum_{h \in \mathcal{H}} \alpha_i^h \hat{S}_i^h$ denotes the residual renewable energy cost at the end of each stage for household i, where α_i^h is a weighting coefficient measured in cents/kW. This cost could be used as a metric in a monetary unit to express the value of residual renewable energy in household i at each time slot h.

The payoff vector is defined as $r = (r_1, \ldots, r_N)$, where $N = |\mathcal{N}|$, which represents the utility that the households receive in the game. Each player has a discount factor $0 < \beta_i < 1$ and it is assumed that this discount factor is the same for all households. $\mathcal{T} = \{1, \ldots, T\}$ denotes the finite history of length $T = |\mathcal{T}|$ that the repeated game is being played. The stage game is the game played at each time period $t \in \mathcal{T}$. The payoff of player i from playing a sequence of actions in history of length t (i.e., $s^1, \ldots, s^t, \ldots$) is given by the following discounted reward formula:

$$r_i = \sum_{t \in \mathcal{T}} \beta_i^t u_i(s^t) \tag{4}$$

There are two equivalent interpretations of the discount factor. One interpretation is that household i cares more about its power cost reduction in the near future than in the long term. The other interpretation is that the household cares about the future just as much as the present, but with probability $(1 - \beta)$ the game may end in any given round.

3.2 Equilibrium strategy design

In the proposed repeated power sharing game households are assumed to have patience and a long-term relationship to each other, which makes their strategic behavior different from that of a one-shot game. That means that they have a long-term plan to reduce their cost. Repeated play allows each player's move to be contingent on the opponent's prior move, and thus each household must consider the reactions of its opponent in making a decision. The fact that the game is repeated allows the players to agree on a certain sequence of actions and punish the players that deviate. The agreement among households is a set of rules to cooperate and lend/borrow each other some amount of renewable power. If two households cooperate, their long term benefit of cooperation may outweigh the short-run temptation to defect. Thus, it can lead to a lower cost for all households in a long-term. The most dramatic expression of this phenomenon is the celebrated "Folk Theorem" [19,20]. The Folk Theorem (Theorem 1) asserts that any feasible individually rational payoff can arise as a Nash equilibrium of the repeated games, if players are sufficiently patient.

Theorem 1 (Folk Theorem) *Consider a finite normal form game $\mathcal{G}$, let $s = (s_1, \ldots, s_N)$ be a Nash equilibrium of the stage game $\mathcal{G}$, and let $s' = (s'_1, \ldots, s'_N)$ be a feasible alternative strategy of $\mathcal{G}$ such that: $u_i(s') > u_i(s), \forall i \in \mathcal{N}$. There exists some discount factor β sufficiently close to 1, such that $\beta_i \geq \beta, \forall i \in \mathcal{N}$. Then there exists a subgame perfect equilibrium (SPE) of the infinitely repeated game $\mathcal{G}(\beta)$ that has s' played in every period on the equilibrium path.*

According to Folk theorem, a household can play s' as long as its opponent has played s' in the past as well. If a household does not consider future and wants to maximize its utility at the current time slot by deviating and switching to a strategy s''_i, its opponent switches in the next time period, for a specified number of periods, to a strategy that minimizes the opponent's maximum payoff (i.e., to the strategy s). There are some famous punishment strategies in this case. One example is the strategy "Tit-for-tat" [21] in which players start out cooperating. If the households' opponent defected, the household defects in the next round. Then it goes back to cooperation. In contrast, in the "Grim Trigger" strategy [20] players start out cooperating. If the opponent ever defects, the households defects forever. However, it is proved [19,20] that deviation is not beneficial if every player has a high enough discount factor β_i given by:

$$\beta_i \geq \frac{M}{M+m} \tag{5}$$

where M is the maximum gain from deviation and is calculated as follows:

$$M = \max_{i, s''_i} u_i(s''_i, s'_{-i}) - u_i(s') \tag{6}$$

and m is the minimum per-period loss from future punishment:

$$m = \min_i u_i(s') - u_i(s). \tag{7}$$

4 Distributed algorithm

In Sect. 3, it is shown that a household would be willing to cooperate and borrow/lend some amount of power from/to another household in the microgrid. In particular, we proved via Folk Theorem that a SPE exists and can be sustained if households are sufficiently patient (i.e., the discount factor β is sufficiently close to 1). In this section, an algorithm is provided (Algorithm 1) to be implemented in smart meters, in order to run the game and find the best matching pair, from a pool of households, to play the stage game with. The proposed algorithm gives flexibility to any household to change its matching pair after a certain history according to some metrics (e.g., if a household' opponent defected or if the cost saving is less than a certain threshold). The strength of this algorithm can be summarized in three main points; (1) it is fully distributed, (2) it can be applied in any microgrid scenario regardless of the size and power consumption pattern of participating households, and (3) it allows a fair matching between households.

Assume a set of households $\mathcal{N}$. Each household sets a list of preferences for households of which it prefers to play the game with. This is done based on the Eculidean distance between the household's average additional demand vector $\overline{\hat{D}}_i$ and the average surplus renewable power vector $\overline{\hat{S}}_j$ of each household in the past history (e.g., last week). The Eculidean distance $(d_{i,j})$ between household i and household j is calculated as follows:

$$d_{i,j} = \sqrt{\sum_{h \in \mathcal{H}} |\overline{\hat{D}}_i^h - \overline{\hat{S}}_j^h|^2} \tag{8}$$

After that, each household defines a list of preferable households sorted in a descending order. The greater the distance between $\overline{\hat{D}}_i$ and $\overline{\hat{S}}_j$ is, the better is the matching between i and j. These lists are used as an input in Algorithm 2 to find the best matching pairs based on Gale–Shapley algorithm [22] (i.e., also known as stable marriage algorithm). The output of Algorithm 2 will be used in Algorithm 1 to run the repeated game between the selected pairs for a certain number of time periods T. In the repeated game, the selected pairs will play cooperate (C) in each stage of the game. After T time periods, each household i will calculate its discounted payoff $(r_i(s'))$ and compare it with the payoff in the case of not cooperating and purchasing the entire additional demands from the grid $(r_i(s))$. If a cost saving is not achieved [i.e., $r_i(s) < r_i(s')$] or if it is less than a certain threshold $(r_i(s') < \varepsilon)$, household i will stop cooperating with its current pair and will enter Algorithm 2 to find another matching pair to play the game with in the following time periods. Households whose pairs defected and broke the relation will also enter Algorithm 2. The rest of households will keep playing and cooperating with the same pair in the next stage game.

5 Simulation results

In this section, the simulation results are presented and the performance of the proposed distributed algorithm is evaluated. In the considered microgrid system there are $N =$

Algorithm 1 A distributed algorithm executed by N households.

1: For each household i calculate $\overline{\hat{D}}_i$ and $\overline{\hat{S}}_i$ in the past week
2: Calculate the Eculidean distance matrix d between the N households
3: Sort each row in d in a descending order
4: Run Gale–Shapley algorithm (Algorithm 2) to find the best matching households based on d.
5: Run the game between the selected pairs and repeat it for a certain number of time periods T (e.g., one week), and allow the selected pairs to play cooperate (C) in each stage
6: Calculate the payoff $r_i(s')$ after T
7: **if** $(r_i(s) < r_i(s'))$ or $(r_i(s') <$ threshold$)$ **then**
8: Defect and leave the stage game
9: **else**
10: Keep cooperating with the same pair in the following time periods
11: The defecting households and their corresponding pairs go to step 1

Algorithm 2 Gale-Shapley (stable marriage) algorithm.

1: Set all households to be free
2: **while** i is free and prefers to play the game with j **do**
3: j= first household on i's list to whom i has not yet proposed
4: **if** j is free **then**
5: (i,j) becomes a pair
6: **else**
7: some pair (k, j) already exists
8: **if** j prefers i to k **then**
9: k becomes free
10: (i,j) becomes a pair
11: **else**
12: (k,j) remains a pair
13: **Return** the vector of pairs which are going to play the game and cooperate during the next week

Table 1 The selected classes of households and their corresponding average annual consumption

Class	Household area (m^2)	Average annual demand (kW)	Number of households in the microgrid
Class A	81	3076	3
Class B	68.5	2384	3
Class C	47.5	2066	3
Class D	67	1714	3

12 households that run the algorithm and play the repeated game. A time period represents one day and is divided to $H = 12$ time slots (i.e., 2-h time slots). For the electricity hourly pricing tariffs, we use the electricity market spot price for Stockholm, Sweden, where data is retrieved from Nord Pool Spot [23]. Simulations are done based on real demand data for residential households of different sizes and consumption patterns in a neighborhood in Stockholm, for the year of 2013. The considered classes of households are listed in Table 1.

It is assumed that the $N = 12$ households have a solar PV system, as an on-site DER, with the same capacity, material and installation settings, and that they generate a similar amount of renewable power with little variance (i.e., all households are in the same area). Real hourly AC solar power measurements for 1 year is used, which is

Table 2 Solar PV system and performance data

Parameter	Value
DC system size (kW)	1
Location	Stockholm, Sweden
Module type:	Standard
Array type	fixed (roof mount)
Array tilt (deg)	20
Array azimuth (deg)	180
System losses	14
Invert efficiency	96
DC to AC size ratio	1.1

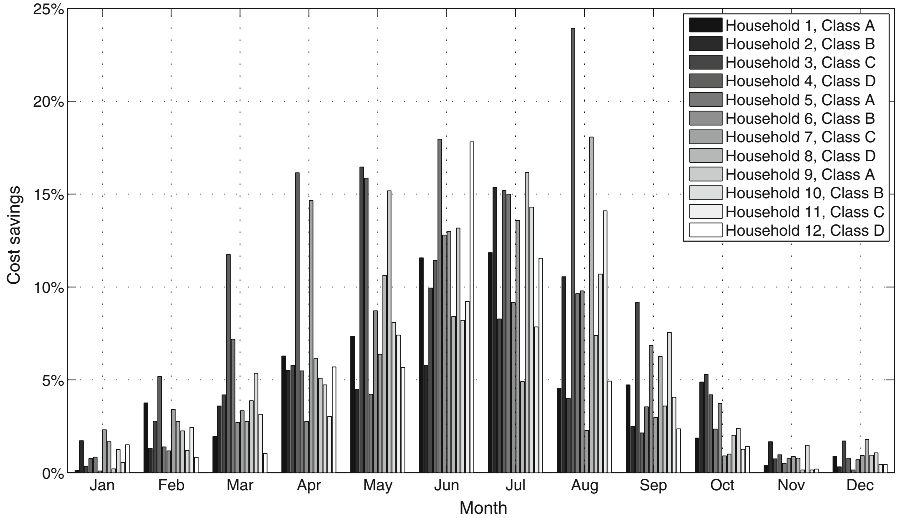

Fig. 2 Average weekly cost savings for each household in every month

outputted from a 1 KW solar PV system applied in Stockholm with the characteristics listed in Table 2. The renewable power of each household i at each time slot h and each time period t is selected from a normal distribution with the mean value of the solar AC power output and the standard deviation of 0.05 kW. In Stockholm, the beginning of solar panel energy harvesting, the energy peak and the end of harvesting differs a lot from season to season. Thus, the harvested energy varies in different months as well as in different days according to weather conditions.

In order to evaluate the benefit of the proposed framework, the distributed power sharing algorithm is applied on the $N = 12$ households for 1 year. As mentioned in Sect. 4, Algorithm 1 is run at the end of every certain and periodic amount of time periods (e.g., 1 week or 1 month). In Fig. 2, the economical impact of the proposed distributed framework on each household participating in the power sharing game is illustrated. It is represented by the average weekly cost saving in every month. In this experiment, we assume that households do not consider the value of their residual renewable energy in the utility function (i.e., $\alpha^h = 0$). It is also assumed that all households are rational and willing to cooperate. The case in which households have an intention to cheat is out of the scope of this paper. When initializing the simulations (i.e., the first week of the year only), random pairs of households are set. After that, households are allowed, by Algorithm 1, to make a decision to continue playing the game with the same pair or to defect and look for another matching pair for the following history of time periods. In the simulation, households are allowed to do that at the end of every week. The decision is based on the achieved cost saving x_i, which is calculated as follows:

$$x_i = \frac{r_i(s) - r_i(s')}{r_i(s)} \tag{9}$$

where s and s' denote to the strategies of playing Defect (D) and Cooperate (C) in the recent history of time periods T (i.e., last week), respectively. In Fig. 2, households are allowed to defect if no cost saving has been achieved. A grim trigger strategy is proposed to determine the SPE, and the discount factor is set to be very close to one ($\beta = 0.95$). After that, the average weekly cost savings is calculated. As shown in Fig. 2, due to the variability in power demands and power consumption patterns of households, a household can reduce the cost of its additional demand up to 20 %, in some annual periods, by borrowing/lending an amount of renewable power from/to another household in the neighborhood everyday instead of always purchasing the whole additional demands from the grid. It is worth noting that the cost saving is achieved by sharing the surplus renewable power only. Households satisfy their demands from their renewable available power first and after that if an amount of renewable power remains, which may be lost if households do not consume it, they share it with a neighboring household.

An alternative method is to allow households to defect if the cost saving x_i achieved is less than a certain threshold ε. Figure 3 illustrates how the number of defecting households changes, as the game evolves temporally, for different cost saving thresholds ε. Every game iteration represents a time period (i.e., 1 week) during which the repeated game between each pair of households has been daily played. It is shown that when $\varepsilon = 10$ % the number of defecting households is relatively high. For $\varepsilon = 0$, households are allowed to defect when no cost savings has been achieved. Upon defecting, each household will run Algorithm 2 and look for another matching pair to exchange power with during the next week. It can bee also noticed in Fig. 3 that the number of defecting households in the three different scenarios is tightly correlated with the time period of the year. For instance, between April and August (i.e., iterations 15–32), the number of defecting households is comparatively less than other annual periods, since the cost savings in those periods are higher. This is because the renewable energy generation profile is typically much higher in those annual periods in Stockholm.

In Fig. 4, the fairness in the distribution of cost savings achieved between households in every month is compared in two scenarios. In the first scenario (Scenario I), households are allowed to run Algorithm 1 and make the decision whether to continue playing the game with the same pair or not at the end of every week. In the second scenario (Scenario II), the decision to defect or not is taken at the end of every month. The

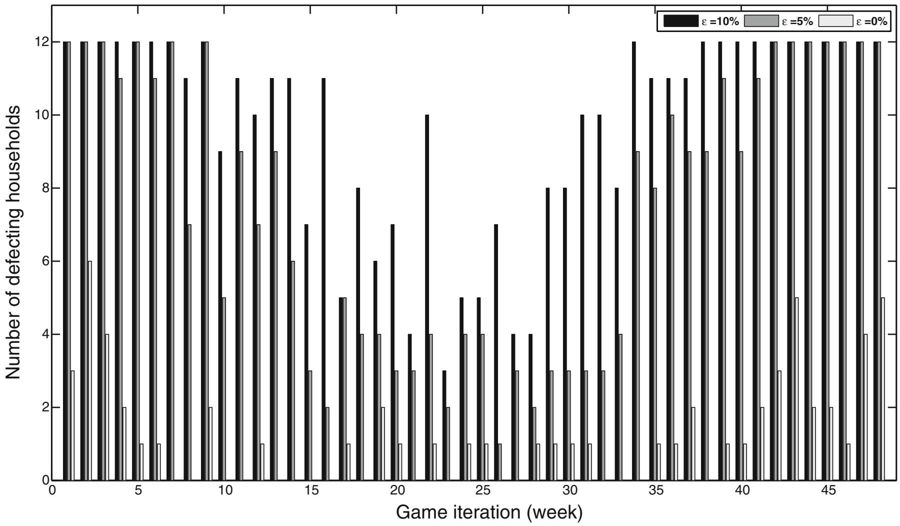

Fig. 3 Temporal game evolution for different cost savings threshold

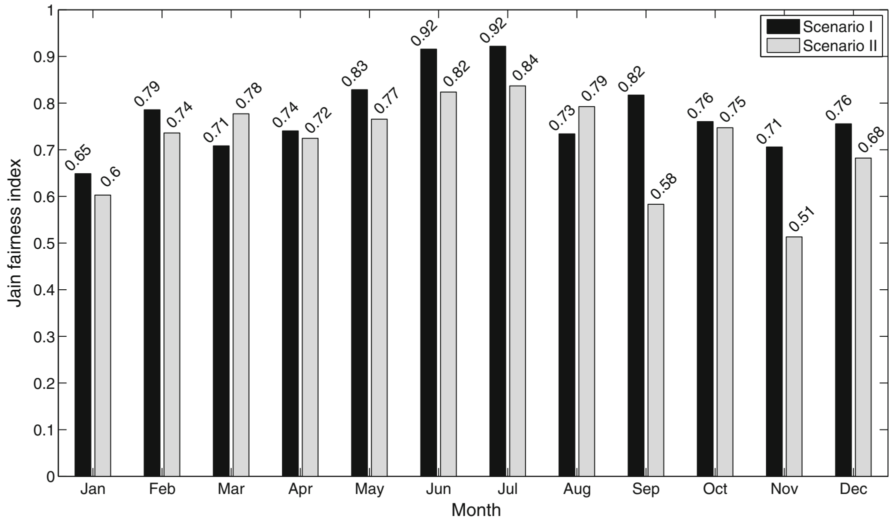

Fig. 4 The fairness in cost savings achieved by all households in the two scenarios. Scenario I: households are allowed to make the decision whether to continue playing the game with the same pair at the end of every week. Scenario II: at the end of every month

Jain fairness index is used as a measurement factor. Jain fairness index is calculated as follows:

$$\mathcal{J}(x_1, x_2, \ldots, x_N) = \frac{\left(\sum_{i=1}^{N} x_i\right)^2}{N \sum_{i=1}^{N} x_i^2} \qquad (10)$$

where $x_1, x_2, \ldots, x_N$ are the average weekly cost savings of the N household at the end of every month. It can be observed in Fig. 4 that in Scenario I if the decision,

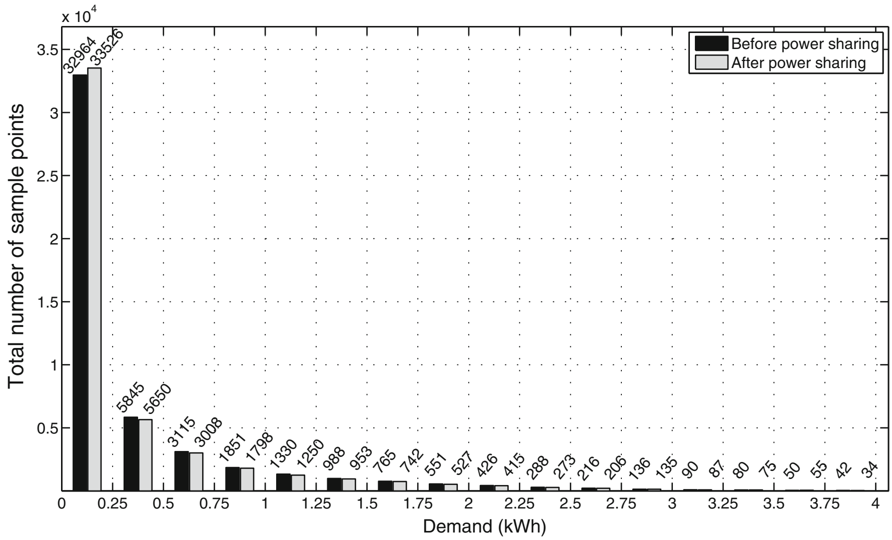

Fig. 5 Histogram of the individual hourly demands of all households in 1 year before and after the proposed distributed power sharing framework

based on the discounted payoff, is made at the end of every week, the fairness in cost savings achieved by all households is relatively higher in most of the annual periods.

Figure 5 shows the histograms of the individual hourly power demands during one year before and after applying the distributed power sharing framework, respectively. It is shown that the individual demands which are higher than 0.25 kW are likely to be greater before adopting the power sharing framework than after. On the other hand, the individual demands which are lower than 0.25 kW are increased after power sharing. This is because a portion of high demands has been satisfied and/or reduced after playing the power sharing game.

In Fig. 6, the monthly environmental impact of the proposed distributed framework is illustrated. The environmental impact is expressed as CO_2 emissions per kWh of electricity demands reduced by the $N = 12$ households playing the power sharing game in the microgrid. The emission factor for Sweden grid electricity is 0.02468 $kgCO_2$ per kWh generated [24]. As shown in the figure, by using the proposed power sharing framework, households can increase the utilization of renewable power and save the emissions that would be produced if they bought their entire demands from the grid.

6 Conclusions

In this paper, a distributed power sharing framework for microgrids based on a repeated game approach is proposed, where households take advantage of the variability in their power demands and consumption patterns to improve the utilization of their locally harvested renewable energy through a borrow/lend scheme.

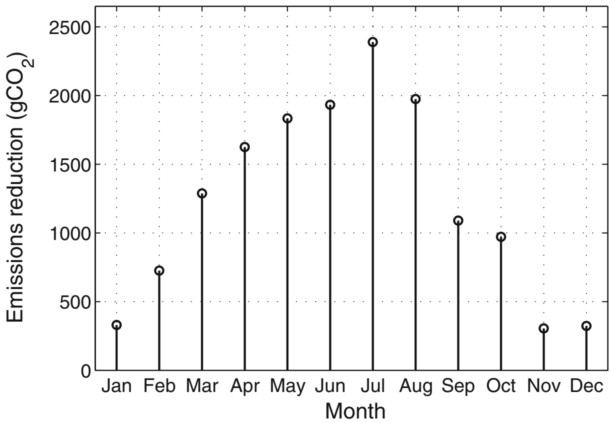

Fig. 6 The CO_2 emissions per kWh of electricity demands reduced by the N = 12 households in the microgrid in every month

The economical and environmental potentials of the proposed framework are assessed based on real demand data and renewable energy generation profiles, as well as real hourly electricity pricing tariffs in Sweden. Simulation results show that households are able to reduce their demand costs by up to 20 % in some annual periods if they share their renewable power and play in a cooperative manner without owning an on-site storage unit. It is also shown that the proposed framework can benefit in reducing CO_2 emissions per kWh of electricity demands.

The study provides valuable insights on how a distributed power sharing framework behave in a microgrid with small number of households and in a place with extreme weather conditions. Besides, it opens the door to some interesting extensions and future research, including a comparison with other centralized frameworks and solutions that improve the utilization of renewable energy. It is also of our interest to investigate the economical and environmental potentials of this framework in areas located at different geographic coordinates and with different weather conditions. In addition, the model allows for extensions to consider that the matching household is able to provide a continuous supply of renewable power for a certain request before sharing it. Finally, selfish behavior and manipulation are also among the interesting problems related to distributed frameworks.

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