Strategic Energy Trading Among Prosumers in a Smart Grid

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***Abstract*—A smart grid (SG) is a network of interconnected nodes that can generate, consume, and share energy. In this paper, we consider a game theoretic approach to its management aimed to balance the monetary and energy transactions between users. We analyze the efficiency of the proposed approach for a smart grid consisting of a set of prosumers connected to an energy router that manages energy and monetary transactions. We compare our game theoretic approach with alternative strategies available to a prosumer, i.e., to sell, buy or store the energy whenever possible. For each strategy, the monetary outcome was compared, showing some interesting results.**

***Index Terms*—Game Theory; Smart Grid; Energy management; Energy harvesting.**

I. Introduction

A smart grid (SG) uses advanced technology and communication systems to improve the efficiency, reliability, and sustainability of electricity generation, distribution, and consumption [1]–[3]. This results in a self-sufficient system resembling the Internet or other self-healing network structures, whose advantages include reducing blackouts and transmission losses [4], integrating renewable energy sources, and harmonzing the management and monitoring of multiple devices so as to obtain real-time data analysis [5], [6]. The participation of users playing the double role of consumer and producer (often dubbed "prosumers") in the grid is strongly encouraged and transactions between different prosumers are allowed, as they may improve the overall system benefit [7]–[9].

This results in a complex system behavior, for which several proposals exist in the literature pertaining to its optimization and management [10], [11]. However, the perspective is often holistic, i.e., the improvement of the smart grid is sought in economic or energy terms, considering the system as a single entity, and formulating the problem as an optimization with a single objective function. Unfortunately, these approaches do not consider that SGs consist of multiple entities with different objectives. To overcome this problem, different methodologies are employed and one of them is represented by game theory that studies the interaction among rational players [12]–[14]. In this paper, we propose a game theoretic approach for the specific purpose of managing an SG with a proper balance of energy and monetary flows of all participants of the system.

In general, game theory has been successfully applied to many network scenarios since it is an effective way to combine different objectives of multiple agents interacting in an selfish way [15]. For the case of smart grid networks, the majority of the approaches adopt a non-cooperative framework to model interactions among players [8]. The problem is often formulated as a trading by different prosumers of their stored energy in a double auction market, with multiple buyers and sellers [9]. In this case, a proper modeling of the utility function of the players is key, and game theoretic approaches accounting for the tradeoff between profits and costs are shown to perform better than greedy algorithms [13]. Another way of modelling an SG system has been proposed in [7] and [16], where power stations and prosumers interact as leaders and followers inside a Stackleberg game [17].

Micro-grids, instead, represent a setup of internal trading among prosumers or between interconnected micro-grids [18]. In [19], an optimization approach for energy transfer is presented, to guarantee that nodes will not be depleted during operation and the energy demands will be satisfied but not exceeded. This can be further extended to game theoretic models for real-time energy trading between interacting prosumers, for example as a Stackelberg game with energy sellers being leaders and energy buyers who are the followers [20]. Pricing competition is then modelled as a non-cooperative game among sellers. Finally, in [21] a model of economic incentives is suggested for market participants who cooperate in developing a micro-grid. The results show the impact on prices and costs for all players in different scenarios, so as to avoid micro-grids failures and maximize the benefits of the involved users.

In this paper, we consider a binary interaction between two prosumers, which is further expanded to an N player scenario, where prosumers are strategic agents trying to optimize their energy and monetary balances in a static game. This approach is compared with strategies where the nodes just always buy, sell, or store their energy, showing a significant advantage towards the individual optimization of the utility. This motivates us to explore intelligent solutions for a local maximization of objectives of the individual nodes and may open new avenues for game theoretic applications in this field [14], [22].

The rest of this paper is organized as follows. The game theoretic framework of the problem is given in Section II. To verify and analyze the efficiency of the proposed approach, we performed a numerical analysis whose results are reported in Section III. The paper is concluded in Section IV.

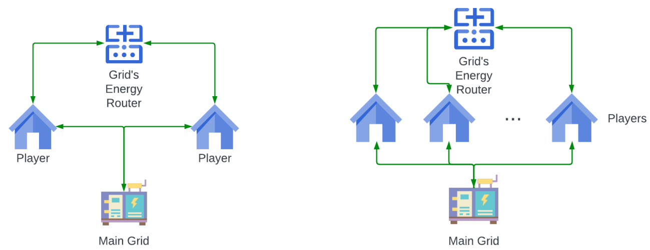

Fig. 1. Schemes for the 2 player game (left) and the N player game (right).

II. GAME THEORETIC SETUP

We consider a smart grid, whose prosumers are capable to generate and store energy by harvesting it from renewable sources [23]. A visual representation is given in Fig. 1. The prosumers can either exchange energy among each other and/or with the main grid. The set of prosumers is divided on two groups: connected to the main grid (ongrid) and those who have no access to it (offgrid). The smart grid acts as a router, to which prosumers communicate their own demand or supply. Having a router allows to track various attributes such as energy availability, amount of sold energy, and energy price.

We consider a discrete time axis. In each time step, prosumers can independently choose one of three possible actions: to store, to buy, or to sell energy [7], [23]. Every prosumer decides the action to be taken based on its current status. The grid manages each request according to the overall demand and energy availability, while the chosen policy defines the payout to each player.

The set of attributes of every prosumer includes: (i) the amount of stored energy, which must satisfy the constraint of being within the accumulator capacity; (ii) energy production; (iii) energy consumption; (iv) monetary balance, which is strictly related to the transactions made with the grid. The status of each attribute is monitored and updated in every round.

We start by considering a scenario with two players. The strategy set of a player is $S = \{buy, sell, store\}$ described below:

STORE: The player stores the generated energy in its accumulator. If the accumulator reaches its capacity the excess energy is directly sold to the main grid and not to other prosumers. Instead, if the player decides to store energy and its consumption exceeds the total energy available, the needed energy is directly bought from the main grid.

BUY: The player buys from the grid or other prosumer, deciding the amount to order, and the smart grid handles the request by either giving energy from other prosumers, the main grid or a combination of the two.

SELL: The player sells energy to the grid, choosing the amount being sold and the smart grid handles the transaction.

TABLE I
PRICE RATIO TABLE

Type of exchange	Price Ratio
Buy energy from the grid (G_b)	1
Buy energy from other prosumers (P_b)	0.75
Sell energy to the grid (G_s)	0.75
Sell energy to other prosumers (P_s)	0.5

Each player has no knowledge of the attributes of other players, and has no access to the chosen strategy of another player. Each player has access to the information provided by the router like energy price, and is fully aware of its own production, consumption, and stored energy at each time frame. This information is private for every player [12].

We start by considering a single-stage game, which will be further extended as a repeated game with T time instances. In the former case, the game is framed as *static*, which implies that it is either just played once or alternatively there is no memory of previous strategic decisions. To outline the utilities of each player, we denote the attributes of every player as including the amount b_0 of available energy before any strategic interaction between players; the produced energy to be stored G_prod; the energy G_b bought from the grid;' the energy P_b bought from other prosumers; the energy G_s sold to the grid; and finally, the energy P_s sold to other prosumers.

We introduce a conditional variable x to avoid negative levels in the energy storage, as

$$x = \begin{cases} 1 & \text{if} \begin{cases} b_0 + G_{prob} \geq 0 \\ b_0 + G_\mathrm{b} + P_\mathrm{b} - 100 \geq 0 \\ b_0 + G_\mathrm{b} - 100 \geq 0 \end{cases} \\ 0 & \text{otherwise} \end{cases} \tag{1}$$

The inequalities above trigger the possibility to sell the excessive energy to the grid, i.e., we set $x = 1$. The aim for each player is to maximize its profit from a monetary point of view, therefore the following rules are applied, where p_e is a price per unit of energy, and $balance^{(i)}$ is the amount of available energy at a current time step i before initiating the strategic interaction, so that $balance^{(i)} = b_0 p_e$:

$$\begin{aligned} \Delta^{(i)}_{balance} &= p_e(\,0.75P_\mathrm{s} + 0.5G_\mathrm{s} - 0.75P_\mathrm{b} - G_\mathrm{b}) \\ balance^{(i+1)} &= balance^{(i)} + \Delta^{(i)}_{balance} \end{aligned} \tag{2}$$

Parameters P_s, G_s, P_b, G_b follows the rules above. The price of energy is different if being bought or sold from grid, or from other prosumers. The ratios between prices per unit are in range [0,1], set to the sample values provided in Table I.

At iteration i, the energy balance is computed as:

$$\begin{aligned} \Delta E^{(i)}_{balance} &= E^{(i)}_{gained} - E^{(i)}_{consumed} \\ E^{(i+1)}_{balance} &= E^{(i)}_{balance} + \Delta E^{(i)}_{balance} \end{aligned} \tag{3}$$

where the energy gained and consumed take into account both the energy produced and used and the energy bought

TABLE II
STATIC GAME OF COMPLETE INFORMATION

Prosumer 1 \ Prosumer 2	Buy	Sell	Store
Buy	$b_0 - G_\mathrm{b} + 0.5x(b_0 + G_\mathrm{b} + P_\mathrm{b} - 100)$ $b_0 - G_\mathrm{b} + 0.5x(b_0 + G_\mathrm{b} + P_\mathrm{b} - 100)$	$b_0 - G_\mathrm{b} - 0.75P_\mathrm{b} + 0.5x(b_0 + G_\mathrm{b} - 100)$ $(b_0 + 0.5G_\mathrm{s} + 0.75P_\mathrm{s})$	$b_0 - G_\mathrm{b} + 0.5x(b_0 + G_\mathrm{b} - 100)$ $b_0 + G_\mathrm{prod} + 0.5x(b_0 + G_\mathrm{prod} - 100)$
Sell	$(b_0 + 0.5G_\mathrm{s} + 0.75P_\mathrm{s})$ $b_0 - G_\mathrm{b} - 0.75P_\mathrm{b} + 0.5x(b_0 + G_\mathrm{b} - 100)$	$(b_0 - 0.5G_\mathrm{s})$ $(b_0 - 0.5G_\mathrm{s})$	$(b_0 - 0.5G_\mathrm{s})$ $b_0 + G_\mathrm{prod} + 0.5x(b_0 + G_\mathrm{prod} - 100)$
Store	$b_0 - G_\mathrm{prod} + 0.5x(b_0 + G_\mathrm{prod} - 100)$ $b_0 - G_\mathrm{b} + 0.5x(b_0 + G_\mathrm{b} - 100)$	$b_0 - G_\mathrm{prod} + 0.5x(b_0 + G_\mathrm{prod} - 100)$ $(b_0 - 0.5G_\mathrm{s})$	$b_0 - G_\mathrm{prod} + 0.5x(b_0 + G_\mathrm{prod} - 100)$ $b_0 + G_\mathrm{prod} + 0.5x(b_0 + G_\mathrm{prod} - 100)$

TABLE III
INITIAL VALUES OF PARAMETERS

Parameters	Value
Accumulator's initial level of energy	50%
Initial wallet balance	500
Probability of renewable source generator for ongrid prosumers	$\frac{1}{3}$ not available $\frac{1}{3}$ solar panels $\frac{1}{3}$ wind turbine 0 solar panels and wind turbine
Probability of renewable source generator for offgrid prosumers	0 not available $\frac{2}{5}$ solar panels $\frac{2}{5}$ wind turbine $\frac{1}{5}$ solar panels and wind turbine

and sold, therefore:

$$\begin{aligned} E^{(i)}_{gained} &= E^{(i)}_{bought} + E^{(i)}_{produced} \\ E^{(i+1)}_{consumed} &= E^{(i)}_{sold} + E^{(i)}_{expended} \end{aligned} \tag{4}$$

Accounting for all considerations introduced above we can formalize the interaction as a static game whose normal form is displayed in Table II. Nine possible outcomes are shown for the strategic interaction between two prosumers.

We further expand the game by simulating the case where N players are interconnected in SG described in the following section. The scheme of such a scenario is also presented in Fig. 1, on the right side. In this case, the game reported in Table II serves as a stage game for the repeated game [14]. At every round, nodes keep track of their actions, which is reflected in a change of their state. For the sake of simplicity, we just consider stationary strategies that only depend on the status of the individual player choosing its own move. In a more complex setup, the game can be extended to consider also a Bayesian character [12] and possible anticipation of future countermoves, which is left for future research.

III. SIMULATION RESULTS

The proposed framework was simulated for 1000 players during 100 rounds. We set the monetary balance and accumulator initial level of energy to the same value for everyone. This simulation parameters are described in Table III. For each round, parameters as energy production and consumption are randomly set according to a normal distribution centered around 75 units, in order to mimic daily changes. Even though dynamic pricing is an important factor in a smart grids [11], to simplify the formulation we consider a fixed pricing for the energy being bought and sold.

Within each round, players independently choose one of the following strategies.

Game Theoretic (GT) Strategy: The player decides to play the **store** action whenever the accumulator capacity allows it. Instead, if the consumption leads to a deficit not handled by the energy balance and the production the player plays **buy** with the minimum amount required to satisfy the current round demand.
Finally, if the accumulator reaches the maximum capacity in a given round the player plays **sell** with all the excess energy that could not be stored. This strategy exploits players' rationality and is designed so as to limit the probability of bankruptcy, due to the intrinsic penalization in buying or selling more than needed.

Always Buy Strategy: The player plays **buy** whenever possible, satisfying the constraint given by the accumulator's capacity, and buying the maximum amount possible. In any other case, the player chooses the action **store**, hence buying or selling the excess/needed energy directly from the main grid if possible.

Always Sell Strategy: The player plays **sell** whenever possible, always satisfying the constraint given by the accumulator capacity, always selling the maximum amount possible. In any other case, **store** is played, therefore buying or selling the excess/needed energy directly from the main grid if possible.

Always Store Strategy: At every time step, the player simply plays store, thus if any excess energy is available or there is energy needed, it can be bought or sold directly from the main grid.

Randomized Unconstrained Strategy: The player decides an action and the amount of energy randomly.

Playing these strategies could lead to bankruptcy from a monetary point of view. When such a thing happens the player is removed from the game, as it can no longer sustain itself.

The parameters of a game are set for each player and provided in Table IV.

TABLE IV
LIST OF ATTRIBUTES

Initial attributes	Range values
Accumulator capacity	[0,100]
Initial energy stored	[0,100]
Attributes set for each time instance	
Energy production	[0,150]
Energy consumption	[0,150]

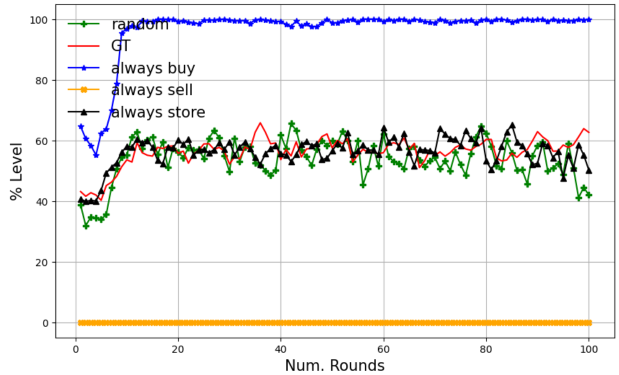

Fig. 2. Comparison of multiple strategies: mean battery level

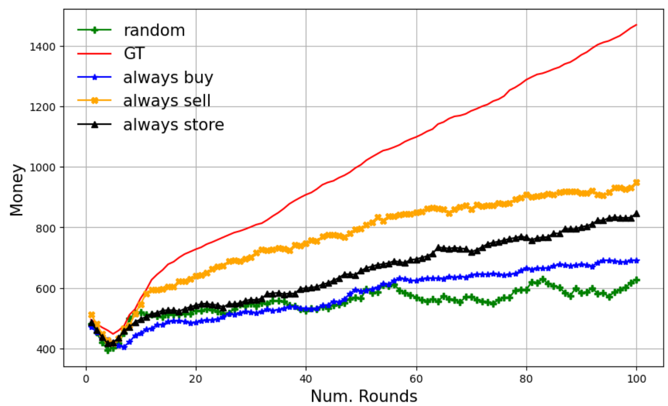

Fig. 3. Comparison of multiple strategies: average wallet

Lastly, to control the distribution of demanded and requested energy by the players, three distinctive policies were introduced: "split equally," "priority queue," and "mixed". "Split equally" implies an equal division of the supplied energy among every player. "Priority queue," instead, prioritizes offgrid players requests. Once these demands are satisfied, the grid manages the ongrid players by prioritizing larger requests. Finally, the "mixed" policy combines the two approaches: it assures bigger requests of offgrid players are prioritized, and then splits the remaining energy evenly between ongrid players.

Firstly, we analyzed the case when all players are ongrid, those strategies are uniformly distributed among them. We computed the average energy level of ongrid players at every round of the game for all three energy split policies presented above. Since adopting different policies do not provide any difference in terms of plot patterns, we chose "split equally" policy as a reference one. Obviously, as it can be seen from Fig. 2 the prosumers adopting an "always buy" strategy have the higher average energy level at each iteration, which leads to a massive imbalance of their monetary state, which can be seen in Fig. 3. Those players who, instead, adopted GT strategy have an obvious monetary advantage.

Further, we performed the simulations for a set of players consisting of 500 ongrid and 500 offgrid prosumers. The

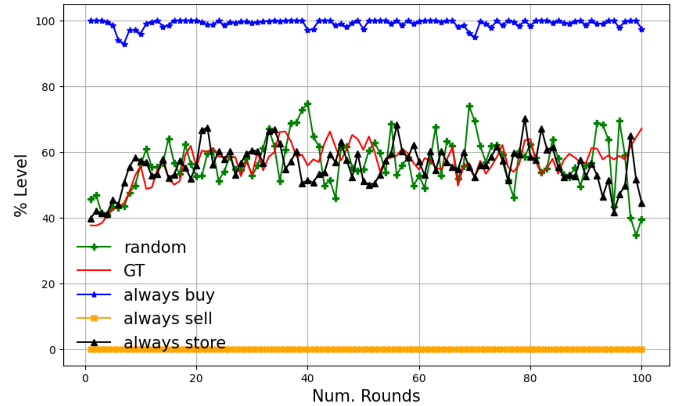

Fig. 4. Comparison of multiple strategies: mean battery level of ongrid nodes

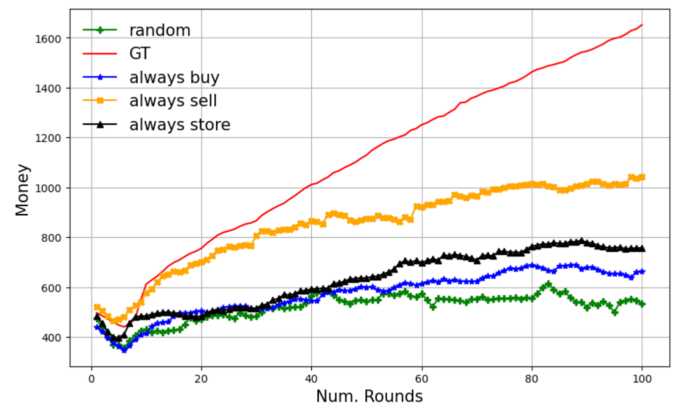

Fig. 5. Comparison of multiple strategies: average wallet of ongrid nodes

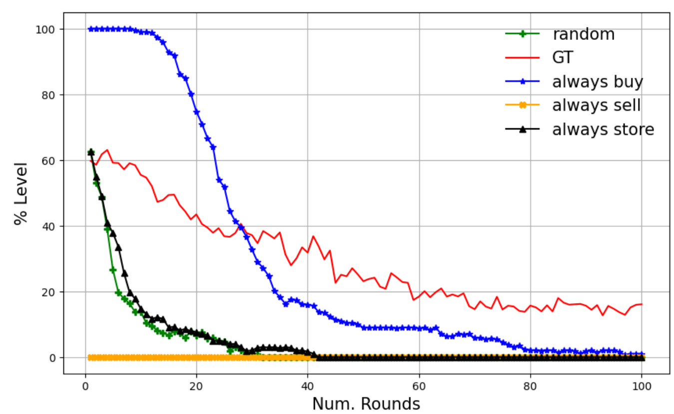

Fig. 6. Comparison of multiple strategies: mean battery level of offgrid nodes

"mixed" policy is chosen as a reference one. Ongrid players preserves the same behavior as in the previous simulations in terms of average energy and monetary level (see Figs. 4 and 5). However, from 500 offgrid players just 24 of them survived till the last round, and the large majority of them were adopting the GT Strategy as depicted from a combined analysis of the offgrid average battery level and wallet graphs as can be seen from Figs. 6 and 7.

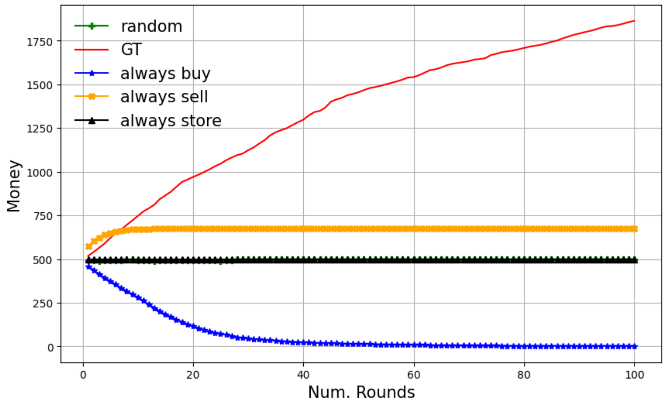

Fig. 7. Comparison of multiple strategies: average wallet of offgrid nodes

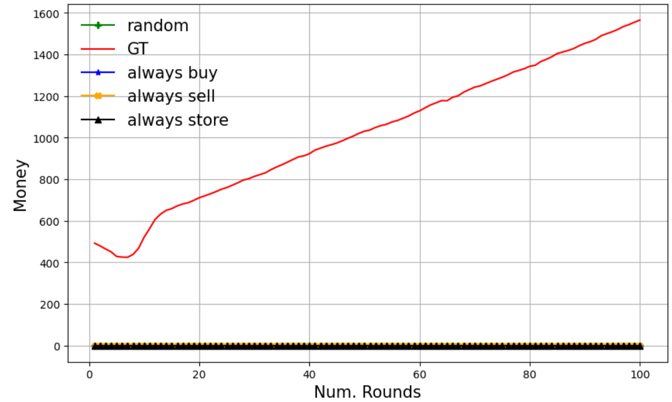

Fig. 10. Only GT strategy: average wallet of ongrid nodes

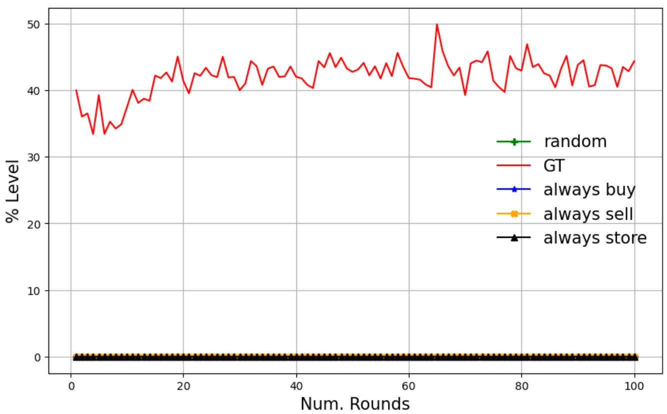

Fig. 8. Only GT strategy: mean battery level of ongrid nodes

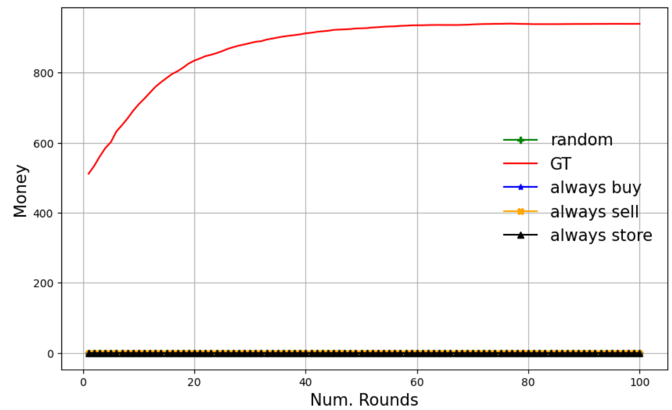

Fig. 11. Only GT strategy: average wallet of offgrid nodes

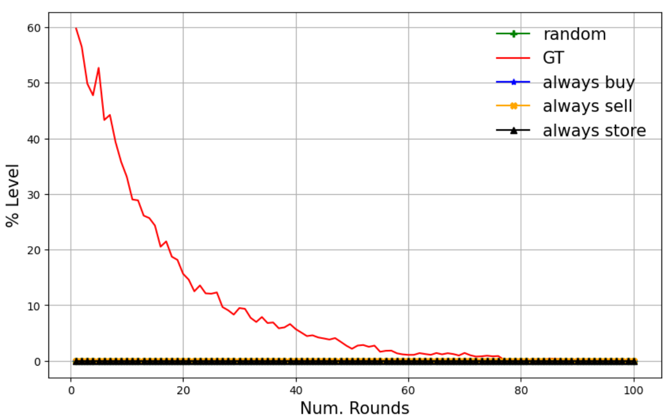

Fig. 9. Only GT strategy: mean battery level of offgrid nodes

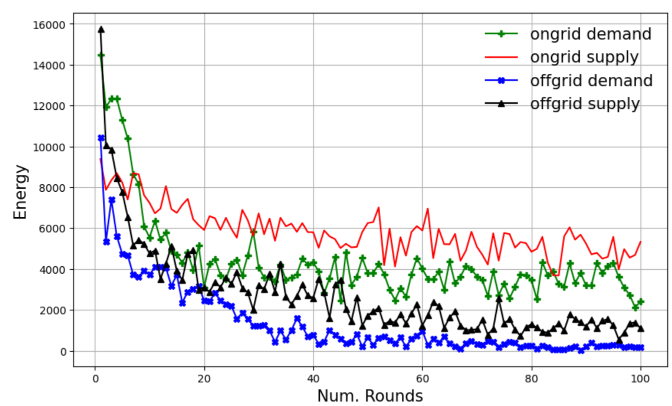

Fig. 12. Average supply and demand

Finally, in Figs. 8–11, we analyzed the case when all the mixed players adopt the GT strategy. To have a complete view of the results, notice that just 295 ongrid players and 104 off-set players reached the final round. We explain this by considering: (i) the analysis of the wallets, showing that the GT strategy allows players to increase their amount of money; (ii) battery level behavior, which is different between players since ongrid ones are able to stabilize it, despite random consumption and production, while offgrid ones struggle to survive due to their exchanges with the grid; (iii) the decreasing number of offgrid players, which leads to a decreasing value of energy demand.

A similar reasoning applies to ongrid players, which is caused by the constant value for supply and demand associates with a drop of consumers. It means that the amount of shared energy is increased comparing with the previous rounds. At the same time the grid was set to play the “mixed” policy, which determines the supply and demand results shown in Fig. 12.

IV. Conclusions

We considered an SG scenario, where offgrid and ongrid prosumers perform money and energy exchanges, among themselves and the main grid. We approached this scenario through game theory, showing results for a static and further, a repeated game. We compared a game theoretical strategy exploiting players’ individual rationality with alternative ones where the players always buy, sell, store, or behave at random. Simulation results demonstrated the advantage of a game theoretic strategy, in terms of balancing money and energy flows.

The scenario chosen could serve as basis for further research by considering dynamic pricing [11], real data distributions for parameter generation [24], more realistic benefit calculations [25], as well as other parameters such as line losses or battery degradation [26], [27], and more.

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