A Game Theoretic Approach for Cost-Effective Management of Energy Harvesting Smart Grids

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***Abstract*—In this paper, we consider energy cooperation in a smart grid scenario. We assume that grid nodes act as prosumers, who can generate energy thanks to harvesting procedures, and exploit the presence of a smart grid gateway that enables energy and money transactions between local and external prosumers. We propose to adopt a game theoretic approach, where the prosumers participating in the smart grid can efficiently improve their revenue. We built a simulator, in which we can tune the smart grid price settings, and compared the game theoretic approach with "always sell" , "always buy," and "random" strategies through smart grid simulations with 500 participants.**

***Index Terms*—Game Theory, Smart Grid, Energy Management, Energy Harvesting.**

I. Introduction

The global scenario is presently showing an unprecedented increase in worldwide energy consumption accompanied with an increment of carbon emissions. Employing renewable sources of energy is one of the solutions that could foster ecology. However, incorporating the usage of "green" energy sources requires the evolution of existing power grid. With the insertion of smart capabilities, renewable sources can be leveraged in an increasingly cost-effective way [1].

The traditional power grid considers unidirectional energy and information flows, where the energy needed by consumers is managed and delivered in a centralized way. The rationale behind smart grids, instead, makes it possible for the customers to actively participate in energy management via an information network [2]. Smart grids, consisting of smart meters and digital technologies, allow customers (households or/and companies) to participate in the exchange by locally buying and selling energy, i.e., to transact with neighbors in the so-called "peer-to-peer trading." This turns communities into self-sufficient systems that are less dependent on the main electrical grid [3]. Since energy is locally generated and distributed, the resilience of smart grid customers is increased, also avoiding undesirable events such as blackouts [4]. In addition, there are other advantages such as reduced line losses, energy transactions that account for real-time data analysis, an ease of local dynamic control, and a possible merge with other Internet of Things (IoT) scenarios [5].

However, there are few challenges related with the diffusion of smart grids, including cyber security threats [6] and especially the issue that this feature of exchanging energy creates various decision-making problems to both consumers and energy providers. For example, consumers may independently decide when to store or sell the energy produced, depending on the energy price. The formulation and solution to this task can be seen from many perspectives. For example, customers and energy providers may be stimulated toward their interdependency [7]. Game theory may deal with this complicated decision-making problem and elucidate the solution from a different standpoint, also keeping the approach based on quantitative reasoning and inherently promoting cooperative network trends [8].

In this paper, we consider a game theoretic approach for smart grid management, in particular, for the money transactions between customers. We simulated a smart grid consisting of a set of participants, a main grid and a router, and we applied different strategies for the prosumers, namely, they can either *always sell* energy, *always buy* it, choose an action at *random*, or follow a game theoretic (*GT*) strategy where they play an equilibrium of the resulting game. We compare the average monetary budget resulting from each strategy and we draw interesting conclusions, in particularly showing that, while selling energy is generally profitable, adding the game theoretic element can further improve the outcome.

This paper is organized as follows. In Section II, we provide a literature review of existing decision-making solutions applied to smart grids. In Section III, we introduce the problem setup, characterizing prosumers and network elements in a quantitative manner. This is further framed in a game theoretic context in Section IV. Numerical results are presented in Section V. Finally, Section VI concludes the paper.

II. Background

A smart grid is a large scale power supply network consisting of many heterogeneous components such as an electrical grid, sensors, communication devices, distributed energy resources, energy storages, and so on. In a sense, it also comprises the participants (energy prosumers), and the whole market. One way to cope with a distributed system consisting of many heterogeneous components is to apply multi-objective optimization, choosing a solution from the resulting Pareto frontier, in which no objective can be improved without sacrificing at least another one [4], [9].

In this context, game theory seems to be a suitable tool for coordinating multiple objectives and conciliating conflicts. Game theory studies multi-agent decision problems that are strategic interactions among independent and rational players, who seek to maximize their benefits [10]. While initially used

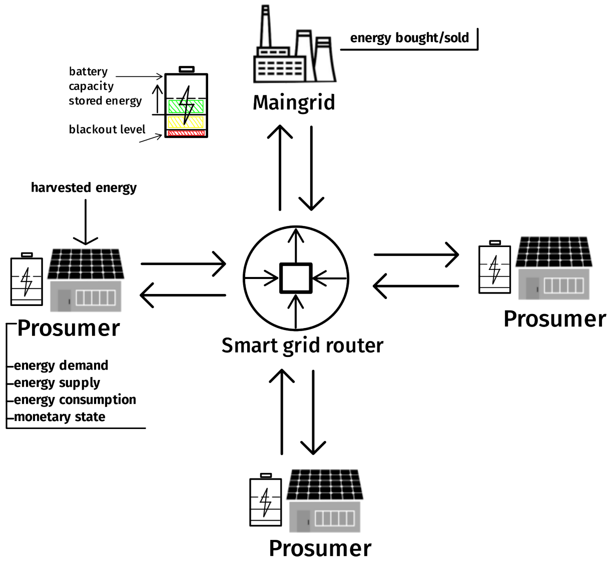

Fig. 1. Smart grid scheme

as a toolkit for economical and political scenarios, nowadays game theory is applied to various areas, in particular, it has recently attracted considerable amount of interest from engineers and researchers working on smart grids [11], [12]. An overview of cooperative and non-cooperative game theory applied to smart grids, its evolution, and future directions are discussed in [13].

In [14], the authors analyze how pricing strategy and game theoretic optimization techniques can be used to optimize the demand response in the smart grid. This was formulated as a binary linear programming problem. Adopting the proposing technique allows to reduce costs by 25%. In [15], the authors design a hybrid advanced metering infrastructure (AMI) for smart grid using game theory, to efficiently save electric power by modelling instantaneous and future prices.

A similar smart grid energy management was studied in [16] where the authors adopt a mixed pricing strategy based on the Rubinstein-Stahl bargaining and a repeated game model. The proposed scheme allows the consumers to make decisions accounting for their power consumption. An alternative objective was presented in [17], where the authors derive a scheduling mechanism accounting for the power consumption patterns of all the individual appliances.

A Stackelberg game approach is proposed in [18]. In particular, the authors model the interactions between the smart grid and consumers, the optimal energy trading parameters are computed analytically at the solution of the game.

Finally, a complex approach for effective energy routing in a smart grid scenario is presented in [19]. The authors introduce maximizing profit strategies to choose the preferable transaction price for both electricity surpluses and shortages. Subsequently, an optimization scheme is adopted to search for an energy route with minimum cost by treating the sale and purchase quantities as transportation supply and demand, respectively.

III. Problem Setup

We consider a smart grid network consisting of a set of participants (so-called "prosumers") that are capable of generating energy by harvesting renewable sources and storing it in their individual accumulators, as well as to exchange it with one another. The prosumers can either perform an energy transaction between themselves or with the main grid. The schematic representation of such a smart grid network is provided in Fig. 1.

The smart grid acts as an individual energy and information exchange router, to which the prosumers report an energy demand and supply at each time instance. Moreover, the smart grid keeps track of diverse attributes such as current electricity price and energy availability.

At each step, participants can sequentially and independently of each other choose one of three actions: to buy, to sell, or to store energy. Buying and selling transactions follow a first come, first served (FCFS) policy, i.e., when a participant chooses to buy energy from smart grid, the latter asks all other participants if they are willing to sell the requested amount of energy. If a prosumer agrees to sell, then the transaction takes place. The cycle repeats until demand is fulfilled or there is no one who is willing or able to sell. A similar procedure is followed when the prosumer chooses to sell energy.

Each prosumer is characterised by a set of attributes, updated over time: (i) amount of stored energy, within the limits of the battery capacity; (ii) energy production, i.e., amount of energy generated by the prosumer; (iii) amount of consumed energy; (iv) monetary state, i.e., balance left after a transaction of either buying or selling energy; (v) amount of energy reserved for a blackout. The prosumer declares its possible energy supply or demand towards the smart grid as

$$\begin{aligned}\Delta = &\text{ current energy level} - \text{consumed energy} + \\ &+ \text{generated energy} - \text{blackout level}\end{aligned}$$

If $\Delta > 0$, the prosumer sends this information to the smart grid as a possible energy supply, otherwise, Δ is announced as energy demand. The last attribute of "blackout level" was set for all participants to the same reserve value, introduced to avoid outages and impose a minimum amount of energy to be stored [4].

IV. Game-theoretic Framework

We frame the problem described in Section III as a repeated game characterised by a set of N players (prosumers), and a set of strategies $S = \{buy, sell, store\}$. Players have no access to previous decisions of other players. Each player needs to decide the strategy to play at his/her turn for each time instance, and can only rely on the information provided by the smart grid, such as the price of energy. Players are aware of their own energy production/consumption, but the corresponding information regarding opponents is hidden.

The extensive form of the game is presented in Fig. 2. In this representation, all strategies are available to the players, but actually, the list of available strategies depends on a current values of the player attributes. The availability of a strategy to a player is defined by following rules.

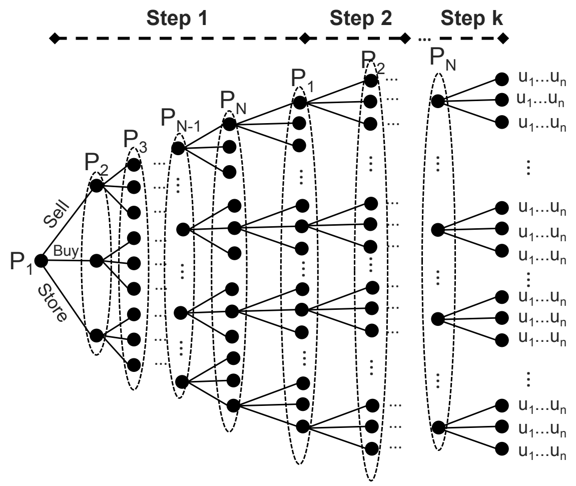

Fig. 2. Extensive form: N players, k steps

TABLE I
PRICE RATES' COEFFICIENTS

Action	Scenario 1 (% from a price rate)
Buy energy from main grid	100%
Buy energy from smart grid:	80%
Sell energy to main grid	50%
Sell energy to smart grid	80%
Store energy to battery when energy is supposed to be bought	0
Store energy to battery when energy is supposed to be sold	65%

Buy: available when energy production is lower than consumption and the storage (excluding the stored energy in case of blackout) is not sufficient to provide the difference.
Sell: strategy available when energy production is greater than consumption or there is an available surplus of energy stored. The participant may sell all surplus of energy produced plus the energy stored minus "blackout" value.
Store: strategy available when energy production is greater than consumption and there is free storage capacity in battery.

The utility of each players is calculated based on the amount of money spent or gained due to buying and selling energy over multiple transactions. The utility function for a player $p \in \{1, ..., N\}$ is defined as

$$u_p = \sum_{i=1}^{T} s_i \cdot a_i \cdot c \tag{1}$$

where a_i is the amount of energy exchanged at a time slot i, $s_i = \{-1, 0, +1\}$ is the chosen strategy that corresponds to sell, store, and buy, respectively. Finally, c stands for the price rate of a transaction. The price rate is diverse for each action that involves energy flows (buy/sell); furthermore, the price rate is also based on whether a player acquired the energy from smart grid or main grid.

TABLE II
RANGE OF PARTICIPANT ATTRIBUTES.

Attribute	Minimum value	Maximum value
Battery Capacity	0	120
Energy stored	0	120
Energy production	0	150
Energy consumption	0	150

V. NUMERICAL RESULTS

We present simulation results for $N = 500$ players, and $T = 100$ simulation rounds. All prosumers start the game with money equal to 1000 monetary units. No discounting factor is applied for a transaction, and money exchanges are performed in the same simulation round as an energy transfers. We compare average money saving of a prosumer after playing one of the four possible types of behaviors: game theoretic (in short, "*GT*", described in Section IV), *always buy*, *always sell* and *random* behaviors.

Always buy behavior is defined as follows:
Buy: available as an expansion of Buy strategy from GT behavior, allowing the participant to buy energy to fill the free storage capacity in a battery;
Sell: available only if there is no free storage capacity in battery to receive the surplus of the produced energy;
Store: available when there was a surplus of energy production that could be stored in a battery.

Instead, *always sell* implies:
Buy: strategy available as in Buy strategy from *GT* behavior;
Sell: strategy available as in Sell strategy from *GT* behavior;
Store: never available.

A. Simulation parameters

We consider a scenario in which the price was chosen such that every smart grid would benefit from incentivize local energy transactions, so that the prices are set as per Table I. In a further experiment, we performed the sensitivity analysis of the solution varying the values of smart grid prices.

Attributes such as energy production and consumption are set randomly at each step to mimic every day behavior changes, with an idea that the weather conditions are not stable and the prosumers do not use the same amount of energy every day [20]. A uniform distribution is used to generate these attributes with max/min of values provided in Table II. The blackout value is set to 20 units.

B. Results

To compare the four behaviors, we evaluate the average money left after T rounds of simulations (see Table III).

One can see that both *GT* and *always sell* strategies are advantageous for the prosumers. If players are only selling, they cover the global consumption demand and there is no need to buy from the main grid; this situation does not occur if the players follow *always buy* or *random*. In addition, in the simulation all players keep the batteries sufficiently charged and are able to prevent a blackout, which takes place when the main grid is asked to provide more than 20 storage units.

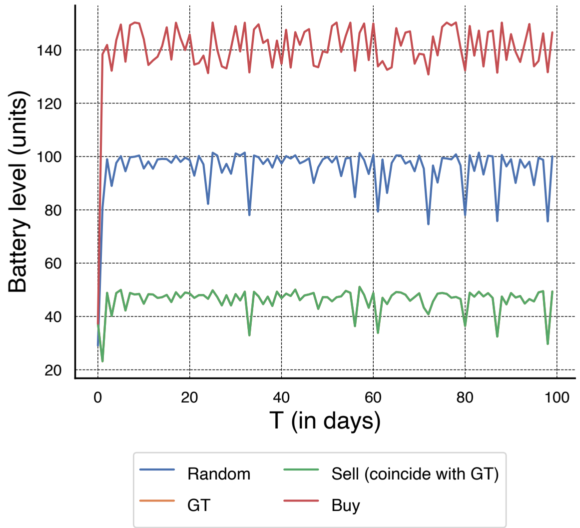

Fig. 3. Average battery levels after 100 simulation rounds

Fig. 3 demonstrates that the players who adopted the strategy *always sell* managed to stay generally above 40 storage units during the whole simulation period.

One can notice that using *always sell* strategy eliminates the need to buy energy from the main grid. Furthermore, due to the sequential FCFS nature of the simulations, the players with lower IDs are usually able to sell to the smart grid, see Fig. 4. Instead, in Fig. 5, the players with higher ID are forced to sell to the main grid, since no more buying players are left. The same dynamics occurs when the players buy energy.

C. Sensitivity analysis

The profit is the parameter that can be dynamically optimized depending on the price rates. In this section, we performed a sensitivity analysis, i.e., evaluated how the values of the price rates affect the average money left.

The search space of price rates is set in a range 0% to 100% of the energy price with 10% linear spacing. The combinations of all possible parameters were generated and evaluated in the simulator in order to gather the final outcome of all scenarios. The final search space was consisting of about 30000 combinations (around 15000 for each general behavior), such that, price per kWh is set as follows:

1) Buy energy from main grid: 0 - 100% of the price
2) Buy energy from smart grid: 0 - 100% of the price
3) Sell energy to main grid: 0 - 100% of the price;
4) Sell energy to smart grid: 0 - 100% of the price.

TABLE III
AVERAGE MONEY LEFT

Strategy	Average money left [units]
Always buy	982.3
Always sell	1056.29
GT	1056.29
Random	1022.91

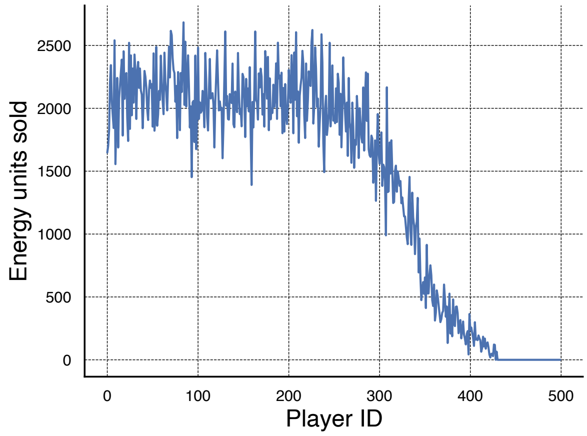

Fig. 4. Energy units sold to smart grid after 100 days by 500 players using strategy always sell

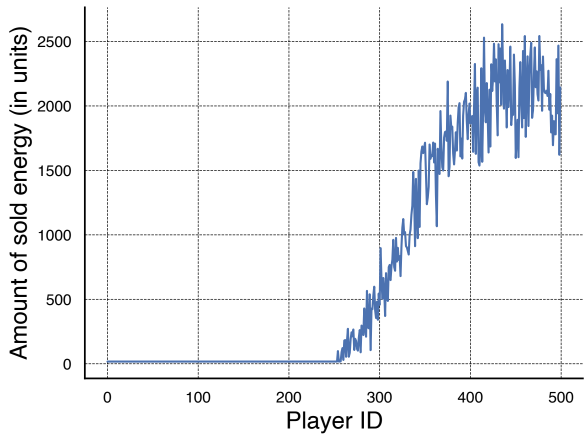

Fig. 5. Energy units sold to main grid after 100 days by 500 players using strategy always sell

Given the size of the search space, the number of players and days that the simulation was performed was reduced, so that the number of players is set to $N = 5$ and $T = 12$ days, respectively. In Fig. 6, the final amount of money left after the simulation runtime is presented, the results are ordered by the "always sell" behavior, i.e., the duplicates that consider all general behaviors were removed. It can be clearly seen that average money left if the prosumers adopt *GT* and *always sell* strategies can be equal for a certain set of parameters, although, GT strategies provides the better results for a wider set of parameters, see Fig. 7. All prices are ranged from 0 to 1, and the order of the x-axis matches that of the results presented in Fig. 6.

The combination of parameters in which the GT strategy provides higher average money left after T rounds in comparison with *always sell* strategy is presented in Fig. 8. This situation occurs when the selling price to main grid is almost zero, caused by the fact that the players does not achieve profit from selling, therefore they prefer to store energy.

In the next experiment, we constrained the space of parameters that correspond to a more realistic scenario, obtained

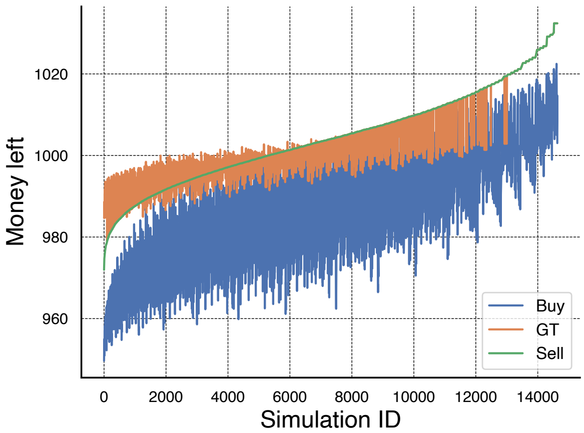

Fig. 6. Average money left for each behavior type for each simulated set of parameters

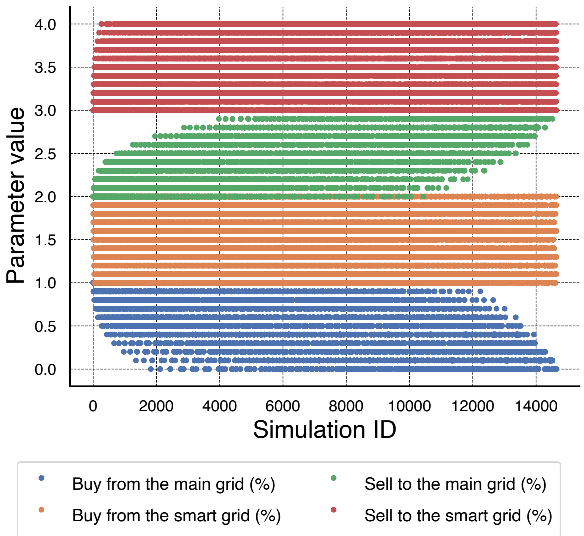

Fig. 7. Values of each simulated set of parameters

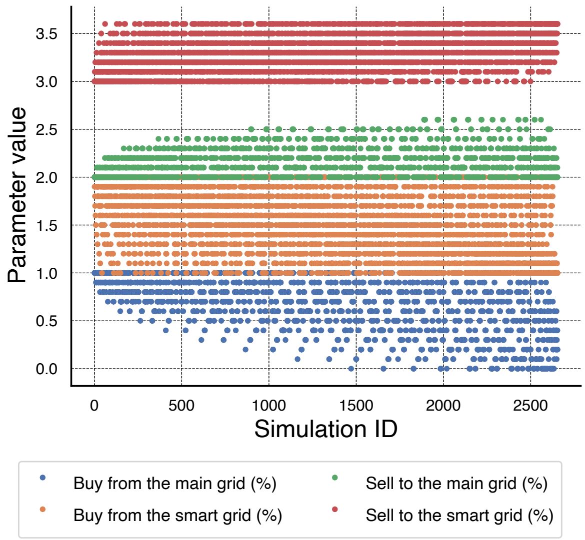

Fig. 8. Values of parameters where “GT” behavior is better than “always sell”

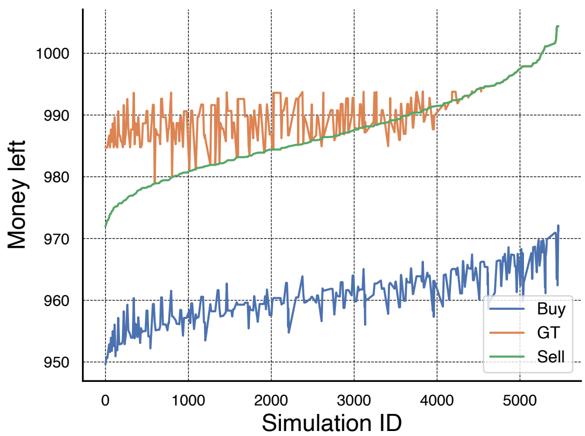

Fig. 9. Mean money left for each behavior in each simulated set of constrained parameters

by imposing constraints, such as the price of buying energy from the main grid being fixed at 100%. Another restriction is imposed on the selling price of energy to micro and main grids, set to be always lower or equal to the price of buying energy in the microgrid, so players could not profit by buying energy from a microgrid and selling back to it, or to main grid. The final search space was reduced to approximately half of all the combinations. Fig. 10 presents the set of parameters offset by 1 for better visualization, all prices are ranged from 0 to 1 as described in the beginning of this section.

The average money left for the constrained set of parameters is displayed in Fig. 9. The order of the x-axis matches the order of the one in the results presented in Fig. 10.

In Fig. 11, the ratio between selling prices to the main grid and the micro grid plotted versus a difference between average money left after adopting *GT* and *always sell* strategies is provided. The negative difference should be understood as a positive profit for the *GT* strategy and the negative profit for the *always sell* strategy. The results for all simulations are presented in Fig. 11 and show that *always sell* might be better than *GT* strategy when the ratio is higher.

VI. Conclusions

We considered a smart grid scenario, where a set of prosumers perform energy transactions among each other and the main grid. Applying game theory for managing the smart grid network can be beneficial, i.e., this approach provides flexibility and easiness in designing and improving a robust smart grid system.

We compared the performance of *GT* with *random*, *always sell* and *always buy* strategies, and found out that in the majority of cases/combinations of parameters, the strategy *GT* provides a higher average money left after T rounds of simulations. The sensitivity analysis also demonstrates that the price rate settings for the energy transactions inside a smart grid affect the expediency of choosing one or another strategy,

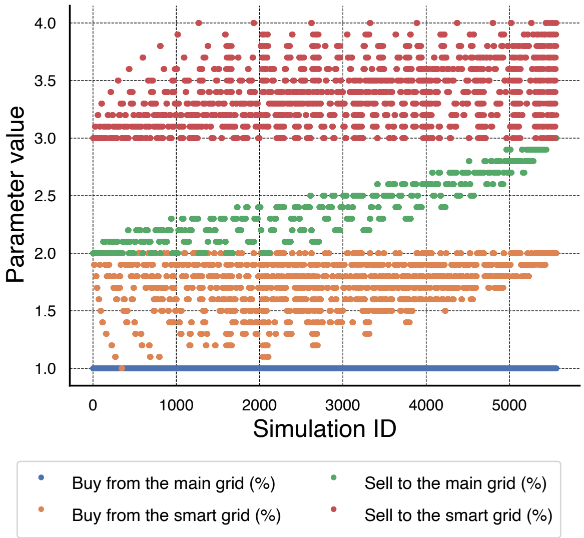

Fig. 10. Values of each simulated set of constrained parameters

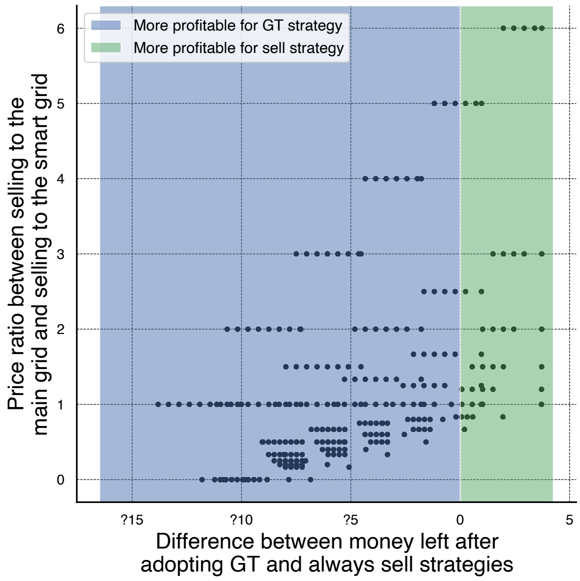

Fig. 11. Ratio between selling to micro and macro prices and difference between *always sell* and *GT*

and the stochastic behavior of variables makes it difficult to have a good estimation without a full-scale simulation.

The simple scenario considered in this paper can serve as a basis for the further development in the area of smart grid systems. However, the simulator can be expanded by connecting real world settings such as pricing and weather data, implementing a simulation step of less than a day [20]. Moreover, a more realstic battery implementation could provide a benefit in terms of accuracy. For instance, one can add the battery parametrization, such as state of health, energy depreciation, and state of charge [21]. The simulator code can be found at [22]. Overall, smart grid have a potential to make energy supply more stable and independent from main power producers by concentrating and managing local resources.

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