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Synchronization Games in P2P Energy Trading

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***Abstract*—The rise of distributed energy generation technologies along with grid constraints, and conventional non-consumer centric business models, is leading many to explore alternative configurations of the energy system. Particularly popular are peer-to-peer energy trading models in which the role of the energy company is replaced with a trustless transaction layer based on a public blockchain. However, to ensure stable operation of microgrids, an energy company is required to constantly balance supply and demand. In this paper, we study the problem that arises from the conflicting goals of prosumers (to make money) and network operators (to keep the network stable) that have to co-exist in future energy systems. We show that prosumers can play large-scale *synchronization games* to benefit from the system. If they synchronize their actions to artificially increase energy demand on the market, the resulting power peaks will force the microgrid operator to use backup generation capacities and, as a consequence, contribute to the increased profit margins for prosumers. We study synchronization games from a game-theoretical point of view and argue that even non-cooperative selfish prosumers can learn to play synchronization games independently and enforce undesired outcomes for consumers and the grid. We build a simple model where prosumers independently run Q-learning algorithms to learn their most profitable strategies and show that synchronization games constitute a Nash equilibrium. We discuss implications of our findings and argue the necessity of appropriate mechanism design for stable microgrid operation.**

I. Introduction

Renewable energy sources, *i.e.*, solar and wind, are the key to tackling global decarbonization [1]. They open new opportunities of large-scale and distributed power generation. First, the local usage of energy results in better power quality by minimizing voltage fluctuations, and reducing line loss [2]. Second, distributed power generation makes the system more reliable and resilient to outages of the microgrid [3]. However, integration of renewables in today's power grid remains challenging. Conventionally, power is generated centrally and flows unidirectionally to passive consumers who pay a fixed price according to contractual agreements with the utility company. Since the energy is consumed directly from its production, during high demand periods balancing supply and demand is necessary to guarantee stable grid operation. Utility companies often have to respond with costly fast energy generation via peak spinning reserves [4], [3].

Transition to distributed power generation and a bidirectional power flow is challenging. Conventional power grid architecture has never been designed to provide the required support neither from hardware side, *i.e.*, in terms of wires and transformers, nor from the overall control architecture [5]. Nevertheless, rapid technological advancements in the following three areas boost the transition towards a smart grid. First, renewable energy sources need to be connected to the network. Their rise is supported by Swanson's law [6], which says that the price for solar panels reduces by 20% for every doubling in produced panels. For example, already now in a typical Belgian neighborhood almost 10% of the households are prosumers [7]. We can expect many more homes to be equipped with solar panels in the future. Second, supporting a network with a growing distributed generation capacity requires a matching capacity for energy storage. Falling battery costs [1] give additional flexibility to the network to address the demand-side response and open new economic opportunities for storage technologies. Finally, decentralization processes in other domains, including financial systems [8] and the Internet [9], created technologies such as blockchains, smart contracts, and trustless systems, crucial for decentralized control of future power systems.

Conflicting Interests. Peer-to-peer (P2P) energy systems promise to balance supply and demand in a real-time, autonomous, and decentralized manner. They give the advantage of promoting distributed and flexible energy generation controlled by their owners, however we need to ensure the overall system also benefits stability of the grid infrastructure. There are conflicts of interests between setting up efficient market mechanisms for people trading energy (*trading layer*), and what is needed in terms of management of the network (*network layer*) [10]. One conflict example addresses *locality* of energy generation and consumption. Energy trading can be set up though the Internet at global scale to enable energy trading with people next door or in another country. This benefits energy generators by promoting uptake and adoption of renewable technologies, but makes little sense from the network management prospective. In contrast to energy trading realized by *virtual* money transfer, the underlying energy network comprises *physical* infrastructure and requires balancing the energy coming into the network and that coming out in real time. From the smart grid prospective, we want to make sure that energy trading happens as locally as possible. This conflict has been broadly addressed in the literature mainly from the game-theoretical point of view and led to a variety of energy trading models with their optimal strategies for local energy trading [11], [12], [3].

Problem Statement. Another conflict, studied in this paper,

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arises from the shift of the focus to *power* (*i.e.*, instantaneous energy generation and consumption measured in watts) rather than energy (in watt hours), as the driving cost factor in the new generation of energy systems [13], [14]. The reason is two-fold: 1) renewables have high capital and low operating cost, yet generation is intermittent, and 2) power network has constrained capacity which directly impacts the energy price. Taking into account *large scale* of power grids in terms of the number of agents, their interest in own benefit (*i.e.*, *selfishness*), and their ability to synchronize their efforts (*e.g.*, by means of software) may lead to unreasonably high power peaks if market mechanisms are not in place. For example, short cycles of synchronous consumption run by prosumers, instead of using own generating capacities, may force activation of energy reserves by network operator to stabilize the network. The inherent artificially increased energy prices benefit generators as they can now enjoy higher profit margins for their energy resource. Efficiency of the described synchronized behavior relies on the high activation cost of the spinning reserves [15] to cope with immediate need to increase network capacity. Synchronization requires little effort but helps prosumers sell their energy at highest price. Few works explore prosumer selfishness in this context. Most relevant is research on incentive mechanisms for demand-side response [16], [10], which would make such synchronization games difficult to realize given large number of consumers. For example, LO3 Energy [17] announced paying consumer for choosing to turn off appliances at peak times, yet providing evidence of purposeful customer behavior is challenging [14].

Contributions and Roadmap. In this paper we study synchronization games in P2P energy systems and show that synchronized behavior of players on the energy market hides huge potential of misusing network resources and can be leveraged by prosumers for their own benefit. This paper makes the following contributions:

- We introduce in Sec. III synchronization games and explain their relevance to distributed energy systems.
- Sec. IV describes simulation of a P2P energy market and shows that selfish synchronized behavior of prosumers leads to highly suboptimal equilibrium system state.
- We discuss in Sec. V what conditions cause undesired behavior and which technologies contribute to it. We conclude the paper with a discussion of mechanism designs that help avoid synchronization games.

As next we put synchronization issue into related contexts.

II. Background and Related Work

Grid Management. Current research intensively evaluates alternative architectures of the power grid to allow easy integration of renewable energy sources and eliminating major issues of the conventional system [18], [3]. Popular models suggest hierarchical structure of the grid composed of interconnected peer *microgrids*. A microgrid comprises smart homes and small-scale local industries that buy energy (*consumers*), sell (*generators*) or both (*prosumers*), yet act as a single entity with respect to the grid. Microgrids can be connected and disconnected from the grid [3]. A *macrogrid* is a network of microgrids and various power generated capacities linked together with high voltage and long distance power lines. Energy flow between microgrids is managed by utility companies.

The main challenge is to balance supply and demand at both micro and macro levels of the grid in scarcity and surplus situations. Solutions to this problem are usually based on better forecasting [19], [20], demand-side response [16], [10], [14] and using interruptible loads [13]. However, there is always a reserved margin of backup capacity that grid operators hold back to respond to a range of factors that could threaten the ability to meet the load. The factors include errors in forecasting, unplanned outages due to plant failures, and transmission outages of power lines and associated equipment [13]. Different types of plants are used to meet each type of load. Low-cost nuclear and coal plants are typically used to meet constant demands in the system. Hydroelectric stations are used as baseload or intermediate load plants. Peaking generators, such as gas turbines or older gas- or oil-fired steam generators, are used to cover for extreme spikes in demand and may be used for only a few hours per year [13]. Peaking plants are expensive to run because they are often less efficient than other types of plants and use more expensive fuel. Network operators use a mix of generators to meet demand at low cost.

Energy Trading. Residential load is conventionally charged by a fixed price while commercial and industrial loads face time-of-use pricing, *i.e.*, prices are high when demand is high [21]. P2P energy markets require new trading models and price formation. Energy trading is defined in [3] as the transfer of energy from an entity that produces energy to an entity with a deficit within a certain time interval. The demand can always be satisfied from the macrogrid, but at a higher cost. The task is to find optimal strategies for each system user such that the overall cost for the community is minimized. P2P energy trading gives several obvious advantages to users: 1) the ability to make personal decision on the type of energy, 2) local usage of energy and as a result less line loss [2], 3) higher system reliability, and 4) seamless integration of renewable energy source and energy storage solutions on the edge. A number of research projects explore energy trading mechanisms [22], [17], [23], [24]. They integrate new technologies such as blockchains and smart contracts, liberalize energy markets by introducing pricing mechanisms based on bidding to provide benefits to renewable energy generators and local energy users. Modeling pricing strategies as an auction is popular in energy markets, *e.g.*, Cournot auction [25], Vickrey auction [26], pay-as-bid auction [27], multi-follower Stackelberg game [28].

Game Theory. A large body of work analyses energy markets from a game-theoretical point of view [11], [29], [28], [12] with the goal to derive optimal strategies for the market players. Energy trading is often modeled as a dynamic non-cooperative game played in multiple rounds. In a non-cooperative setting, all agents learn purely selfish strategies by trying to maximize their own benefit without considering any prior information from other agents. Q-learning [12] and DQN [29] are popular approaches to learn agents' strategies, that result in a Nash equilibrium (NE) [30] in their joint action space where individual utilities are maximized and any unilateral deviation decreases their utility.

In contrast to learning an optimal strategy, mechanism design is concerned with designing games such that certain outcomes are achieved by rational players. Mechanism design has not played a significant role in energy trading so far [3]. This paper highlights the need for mechanism design to avoid undesired outcomes. We show that player synchronization is essential. People's pronounced need to cooperate, which goes beyond rational arguments [31], makes synchronization games even more probable without proper mechanism design.

Synchronization. Timing plays a prominent role in energy network management. Operators perform balancing in real time to ensure stability of the overall energy system. Many research activities are dedicated to solving technical network-layer synchronization issues in power grids to ease integration of renewables and improve power quality [32], [33]. To the best of our knowledge, the study of a synchronized behavior of users received little attention in the research literature.

III. Model and Problem Statement

Microgrid. Consider a microgrid $\mathscr{M}$ with N agents. Each agent in need of energy is either a *consumer* $c \in C \subseteq N$ with no generator or local storage, or a *prosumer* $p \in P \subseteq N$ with generation and / or storage capabilities. Microgrid has a connection to an utility company, which is responsible for maintaining the infrastructure of the grid (the power lines) and keeping the system in a stable state by balancing supply and demand in real time. The time is divided into discrete time intervals $T = \{t_1, t_2, \dots\}$ of a fixed length. For simplicity, we assume that during $t \in T$, there is no change in supply or demand for electricity, and thus the prices for selling, buying, and balancing are fixed. The utility company sets a price s_t dollars per MWh to meet the demand in case of energy scarcity in the microgrid. The price includes the cost of power generation during t, and the cost of network usage, maintenance, and reinforcement of transmission infrastructure.

Backup Energy. Energy suppliers who provide electricity to consumers and businesses buy energy from power stations. To meet the demand, the operator can request more or less generation a few hours ahead of real-time [34]. As part of balancing, each power station makes a bid that reflects what it is willing to be paid or to pay to be taken off or moved on to the network. Network operator makes sure enough *backup power* is available to cover for any potential shortfall during t. Network operators may ask generators (*e.g.*, wind farms, hydroelectric stations) and large consumers (local energy-intensive industries) to come on or off the grid to help balance supply and demand, or to manage grid constraints (bottlenecks) in the network. The availability of the backup power and the price of using it directly impacts s_t. The utility company represented in a microgrid by a *network operator* regulates these balancing costs.

Market and Agents. Each prosumer $p \in P$ has a fixed generating capacity during each time interval t. This is energy available directly from his PV or from his local storage. We assume generation during t is reliable even for intermittent energy sources. Electricity can not be stored in large quantities and thus we assume local storage has very limited capacity. We note that speculations such as filling the storage while the energy is cheap and selling it at a higher price are generally possible. A prosumer p sets the price for his generated energy to $s_t^p < s_t$. Both prosumers and consumers are *rational* and *selfish*: the former use the system to maximize their own profit, whereas the latter buy electricity at the lowest price. Since setting prosumer prices to a higher value than s_t makes consumers buy energy from the utility company, prosumers are interested in artificially increasing s_t during times when their energy resource is easily available despite its intermittent nature.

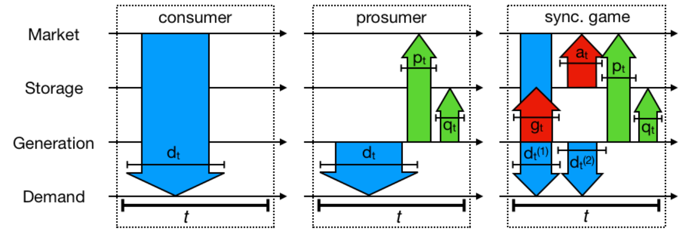

Fig. 1: Consumer, prosumer and a synchronization game.

Since energy supply from each generating station is fairly constant or can be planned in advance, the market is tightest when demand is highest. Consequently, high wholesale prices correspond with high demand. A consumer $c \in C$ buys energy according to his private stochastic demand. There is certain expected periodicity of the demand during the day including morning and evening hours. Consumers buy energy at the lowest price available. We assume energy trading has zero time overhead. Transactions for each t are either put on a public blockchain or in a private ledger maintained by the utility company.

Synchronization Games. We refer to a situation when a group of prosumers $\{p_i\} \subset P$ in a microgrid $\mathscr{M}$ act together to create artificial energy demand with the goal to increase the operator's price s_t as a *synchronization game*. $\{p_i\}$ can achieve mutual synchronization intentionally by means of time synchronization protocols, or without being aware by running malicious software controlled by an adversary.

Consider a synchronization game example depicted in Fig. 1. Consider sufficient sun to fully cover energy demand of each individual household in the region during consecutive time slots $t_1, t_2, \dots, t_n$. Consumer buys electricity on the market to meet the demand d_t and pays the price s_t during time slot t. A wishful behavior of a prosumer p (called *friendly*) is to meet his own demand d_t first, sell any surplus p_t to neighboring consumers and possibly store q_t energy into local storage (p_t and q_t may be zero). The prosumer makes $p_t \cdot s_t^p$ profit. Unfortunately for the prosumer, generator-friendly sunny weather keeps energy price s_t (and thus also s_t^p) low. Now what if prosumers unite their efforts to artificially stimulate the demand and reduce generation? Let each prosumer use a fraction of time to buy energy on the market to meet a part of his demand d_t^1 (at a currently low price s_t) whilst filling the local storage with generated energy g_t. Another fraction of time is used to generate d_t^2 energy for his own needs, while selling a_t from his local storage. The prosumer playing the game should make sure he meets his total demand:

$$d_t^1 + d_t^2 = d_t, \tag{1}$$

and miminizes his loss in the game given by

$$d_t^1 \cdot s_t - a_t \cdot s_t^p \rightarrow \min. \tag{2}$$

Ideally, the above difference equals zero, although a small loss might still be worth playing the game depending on the later reward. Given a large number of synchronized prosumers running the same protocol, an artificially generated electricity demand will be created, followed by a recovery to compensate for the loss by selling electricity from the local storage. High demand peaks will force the network operator to use additional capacities (*e.g.*, low-cost hydroelectric stations and high-cost gas power) to balance supply and demand and stabilise the network. A consequent increase of operator's price s_t starting from a time interval t_k will increase profit margins for prosumers and make them sell generated energy at higher price during $t_k, t_{k+1}, \ldots t_n$. Note that a synchronization game can be played for several consecutive time intervals to empty low-cost backup energy resources. Since moving spinning reserves on the grid comes with a fixed activation cost, increased s_t can be expected to be kept high for a prolonged time period.

Repeated Synchronization Games. Running a synchronization game for one round may not be worth the effort. Prosumers may have to repeat the game for several rounds to benefit from the system. Let's assume the operator makes a small increase Δ_s to the price s_t after one successful synchronization game at t. Although the prosumers playing the game may hurry to increase their electricity prices s_{t+1}^p, they will also increase the probability that they won't be able to sell their energy during the next round due to high amounts of cheap energy available on the market. Let therefore assume the prosumers keep their price $s_{t+1}^p = s_t^p$ but decrease the interval $d_{t+1}^1 = d_t^1 - \Delta_d$ to minimize the game loss. Thus, in the next round of synchronization games the prosumers minimize the following loss function:

$$(d_t^1 - \Delta_d) \cdot (s_t + \Delta_s) - (a_t + \Delta_a) \cdot s_t^p \rightarrow \min. \tag{3}$$

If we assume that the rates of storing a_t and consuming d_t^1 energy are the same, we have the following dependency between the operator's energy cost increase Δ_s and the length of the synchronization interval Δ_d:

$$d_t^1 - \Delta_d = d_t^1 \cdot \frac{x}{x + \Delta_s}. \tag{4}$$

The sum $x = s_t + s_t^p$ is constant. We conclude that the length of the synchronization interval is inversely proportional to the increase of the operator's price. This makes synchronization games possible only up to a certain limit bounded by the synchronization accuracy between prosumers.

IV. Simulation

In this section, we use multi-agent learning to simulate energy trading in a microgrid. In the following subsections, we list parameters that drive our market model and show that prosumers are able to synchronize their efforts to artificially boost the demand and leverage the consequent increase of the operator's price to benefit from the system. The synchronized behavior corresponds to a Nash equilibrium (NE) [30].

Network and Market Parameters. The simulated microgrid comprises $|P| = 5$ prosumers, $|C| = 20$ consumers, and a grid operator. Energy trading market is modeled as a 24h game which repeats daily. We split the time into $|t| = 15$ minutes consecutive time intervals. During an interval t_k, each consumer buys energy on the market according to his private demand curve, modeled as a sum of a fixed and a variable components. The fixed component includes a morning and an evening peak between 6 to 9 AM and 4 to 8 PM [35]. Each consumer has his own habits and thus the peaks are generated at random within the typical times. The variable part is sampled from a normal distribution with zero mean and 15% variance. Consumers are interested in buying cheap energy to meet their demand.

Prosumers extend consumer function with generation capabilities. Each prosumer has several solar panels capable of generating between 245 and 345 Watt of power [36]. There is a generation peak between 10 AM and 6PM throughout a day different for each prosumer. Power generation can vary up to 5% from one moment of time to another. Prosumer's generation curve is his private knowledge. For every time interval t_k prosumer independently picks one of two actions: to either be friendly or to play a synchronization game. If a prosumer decides to be friendly, he uses generated energy to cover his own demand and sells the surplus at the market for the best price he can. If the deal is successful, he increases the price by 10% before the next transaction. If the price appears to be too high and he fails to find a customer, he decreases the price by 10%. Consumers never buy energy from a prosumer if his proposition is more expensive than operator's price. If a prosumer decides to play a synchronization game, he does neither earn nor loose any money but artificially increases the demand in the network by the half of his own demand.

Network operator chooses the energy price $s_{t_{k+1}}$ depending on the new demand $d_{t_{k+1}}$ and is responsible for balancing supply and demand by turning on additional generation capacities if necessary. We assume activation of backup energy sources increases the energy price according to:

$$s_{t_{k+1}} = s_{t_k} \cdot (d_{t_{k+1}} / d_{t_k})^2. \tag{5}$$

The increased price is kept stable for a prolonged time interval (by the end of the day) if no higher demand peak arises. This is reasonable, since most backup energy sources (*e.g.*, gas stations) have high activation cost and can't be shut down immediately.

Q-Learning and Nash Equilibrium. We model prosumer behavior as a Markov decision process [37] over a discrete

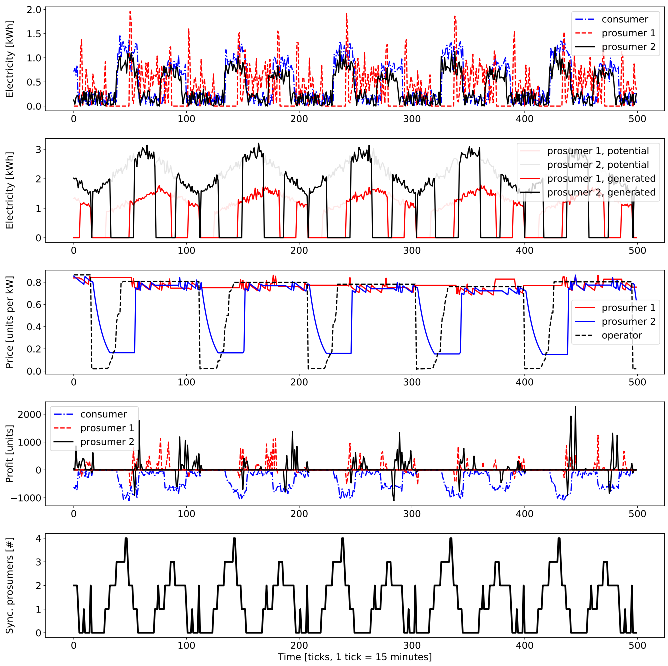

Fig. 2: Market over 5 days on synthetic data (top down): 1) demand by two sample prosumers and one consumer, 2) generation pattern by the same prosumers, 3) operator's and prosumers' prices, 4) profit by the same agents, 5) number of prosumers playing a synchronization game.

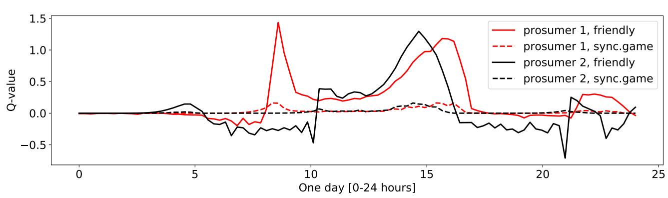

Fig. 3: Learned Q-matrix of two non-cooperative prosumers.

set of states during the day. In the training phase, prosumers independently decide to either behave friendly or to play a synchronization game. The reward is their daily profit given by the difference between earned and spent money units. Prosumers learn their optimal behavior by leveraging a reinforcement-learning algorithm called Q-learning [38]. Despite a non-cooperative nature of Q-learning, prosumers manage learning to synchronize their actions to maximize the benefits. We use default Q-learning parameters: learning rate $\alpha = 0.01$, reward decay $\gamma = 0.9$ and exploration rate $\epsilon = 0.1$ while training. Q-matrix of size (actions $\times$ states) stores decision values based on the obtained accumulated rewards received over the history of training. Q-matrix is updated as follows:

$$Q(t_{k+1}, a_{t+1}) \leftarrow Q(t_k, a_t) + \alpha \cdot (r_{t+1} + \gamma \cdot \max_a Q(t_{k+1}, a) - Q(t_k, a_t)) \tag{6}$$

Learning optimal behavior is time-consuming. In our implementation training phase lasts 520 days, mainly due to randomness in the demand and energy generation, that make the modeled environment stochastic as perceived by each separate agent. Fig. 2 presents testing results over five consecutive days. The two top plots show the demand and the generation pattern of three random agents: two prosumers and a consumer. Each demand curve has two noisy peaks, with the higher one being the daily peak. Power generation is more efficient during the day and drops to zero towards the night. Operator's energy price is a function of the demand and is thus low at night when demand is low. Prosumers try to keep their prices as close to the operator's price as possible. The second plot from the bottom visualizes payments and profits by the agents. When comparing the profitable hours to the number of synchronized prosumers in the bottom plot, it can be seen that no profit is generated in the first half of the morning peak (and sometimes also the evening peak), since during that time prosumers synchronize to artificially increase the demand. This behavior can also be observed in the learned Q-martix by the prosumers depicted in Fig. 3. In the morning, between 5:30 to 7:00 AM and in the early evening, sync. game behavior of prosumers is more beneficial than a friendly strategy. The set of strategies learned by all prosumers makes a NE, which however fails to maximize the social welfare. Artificially generated high demand results in higher energy prices paid by consumers, unnecessary activation of backup energy sources by the network operator, and thus higher environmental footprint, waste of resources, pollution and global warming, which could be avoided.

V. Discussion and Conclusion

We next discuss the research findings from this work and how synchronization games can be detected and prevented.

What makes synchronization games possible? Every energy supplier wants to raise the market price, just as every consumer wants to lower it. While consumers are passive and only have demand-side response at their disposal to lower the price, selfish prosumers may cause significantly more harm to both the network and the market. Given large scale of microgrids, *e.g.*, comprising a city or a town, with a potentially large number of prosumers, synchronization seems easily achievable by means of malicious software. The software may rely on standard time synchronization protocols (*e.g.*, NTP [39]) and promise to increase revenues of prosumers by leveraging participatory approach. Note that people collaborate more often than rational minds would do as research results show [40].

Can we detect synchronization games? Smart meters play a key role in operation and management of microgrids, support energy trading, and may provide valuable data to detect synchronization games. However, smart meters are often imprecise [41], fail to deliver sensor readings at high rates and in real-time (*e.g.*, current smart meters often provide measurement every 15 minutes [42]). Therefore, synchronization games are difficult to detect in today's P2P energy markets under test. Prosumers could always use a fraction of the reporting interval to artificially increase the demand and make synchronization game detection generally hard. We envision that utility companies could use machine learning algorithms to detect synchronization games with high probability based on smart meter reports and transaction lists.

Can we prevent synchronization games? Precise energy metering, real-time reporting, high security standards will help to avoid manipulations. If customers are charged real-time prices, peak demand will be reduced, stimulating reduction of generating capacity [21]. The tighter the reporting interval of energy meters is, the more difficult it gets to stay undetected for selfish prosumers. Syncronization errors and randomness in generation, storage, and switching mechanisms contribute to imperfect synchronization and, thus, flatten artificial power peaks. Real-time metering and trading is needed to detect and prevent synchronization games by minimizing all sorts of data transmission, processing, and storage delays (*e.g.*, in public blockchains). Mechanism design and proper incentive mechanisms play prominent role in preventing synchronization games. For examples, monetizing demand-side response [16], [10] could make synchronization games unattractive. LO3 Energy [17] tests this concept yet faces the difficulty to provide evidence that the load shift was indeed on purpose and not by chance. Another possibility to prevent synchronization games is by making operator price s_t less sensitive to activation and operation cost of spinning reserve and balancing mechanisms. Finally, synchronization games can be forbidden in contractual agreements between utility company and prosumers.

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