Misalignments of objectives in demand response programs: a look at local energy markets

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***Abstract*—Local energy markets (LEMs) have been proposed to mitigate the variability introduced in power systems by distributed renewable energy resources such as photo-voltaic energy. During the progressive release of LEMs, the decision problem faced by prosumers (consumers that might also produce energy), will differ from the wholesale electricity market's one because there is always the alternative to buy from or sell to the utility company. In this setting, guaranteeing that the aggregated energy consumption will be well behaved depends on the properties of the mechanisms used to implement the market, the alternative tariff offered to participants by their utility and how prosumers interact among themselves.**

We present a pathological example of a LEM in which the best strategy for the agents results in unnecessary peaks of demand. A decision model for players participating in LEMs is developed to study the existence of undesirable behaviour while using realistic data and number of participants.

Through numerical experiments, we identify the key aspects of the player's behaviour, strategy and environment that lead to the aforementioned peaks, all under reasonable circumstances. Simple fixes are discussed to overcome the pitfalls of such markets.

I. Introduction

Among demand-response programs, those that incentivize local exchanges of energy, i.e., energy produced in a Low Voltage (LV) grid being consumed in the same LV grid, are of particular interest as they can reduce congestion in the main grid. Local energy markets (LEM) have been proposed as demand-response programs capable of incentivizing local exchanges and several projects are currently under implementation [1], [2].

In this paper, we consider LEMs among residential households. These households have a demand or surplus energy (if they produce more than what they consume) which they would normally settle by buying (or selling) from a Traditional Energy Company (TEC). Furthermore, we examine only LEMs implemented as sequential double auctions in which households can offer to buy or sell energy in the next time-slot (usually 30 minutes). Households that fail to trade in the LEM can decide to trade with the TEC instead. An example of such an architecture was implemented in Switzerland [3].

As the LEM can create more competitive prices than the TEC when there is surplus of local energy, LEMs can serve as demand-response programs by providing more competitive prices.

Our approach is related to [4], [5] in that we model the interaction of agents with both the TEC and the LEM at the same time, while considering a flexible energy consumption due to energy storage. This is in different from other proposals such as Ilic et al. [6] where the authors propose the use of a continuous auction to trade among agents but do not model the intra-temporal flexibility of agents or [7], where grid constraints are considered and there is a model for flexibility but actions are not taken sequentially.

A. Motivation

A demand-response program offers incentives to users to change their consumption. Ideally, such a change is beneficial for both the participants and the power grid. In other words, a good demand-response program aligns the utility of agents and grid operators such that a benefit for one gets reflected in a benefit for the other.

Unfortunately, this needs not be the case for Local Energy Markets. Kok et al. [8] observed that sequential markets do not take into account the inter temporal constraints of consumption and can lead to problems. We explore this issue at depth in this paper but, we begin by presenting a toy example illustrating this phenomenon.

1) Example: There are 4 players (3 buyers and one seller) and 3 time-slots. The 3 buyers need one unit and can get it in any of the 3 time-slots. The buyers can buy their unit in the local market at a variable price, or from the TEC at price 2. The seller has one unit to sell, only in the 3rd time-slot. He can sell it in the market or to the TEC for a price of 1. There is a probability p for each buyer to have 0 demand instead of desiring one unit, those events being independent, and the other buyers know that.

All buyers have an incentive to wait until the last time-slot: there is no loss in doing so (the price of the TEC does not change) and the profit can be bigger (because of the possible lower price in the market, e.g., with probability $p^2(1-p)$ they will be the only buyer facing the seller)

Although this is not necessarily bad for players, this is a bad equilibrium for the grid: it creates a peak in the last time-slot. Also, this outcome is not flexibility-efficient: in the best scenario, each buyer consumes in a different time-slot and the peak is the smallest possible.

The VALADOE Chair of IMT Atlantique in partnership with Télécom ParisTech and Mines Saint Etienne and supported by ENEDIS, Région Pays de la Loire, Nantes Metropole. This publication only reflects the views of its author(s). Neither the ValaDoE Steering Committee nor the associated organizations can be held responsible for the use that could be made of the information contained therein.

B. Contributions

The example presented above points to a gap in our understanding of local energy markets. This problem is related to the coexistence of LEMs with alternative ways of trading energy and, in particular, to how agents plan their schedule with respect to future prices, a topic usually not considered in the literature [9], [7].

The work from Alabdullatif et al. [10] is closely related to our approach. They study a set of agents that participate in a LEM and have the option to trade with a TEC instead. They do not model the scheduling of each player's flexibility as an optimization problem nor they forecast trading prices in the market for more than one time-slot ahead. Because of that, some of the behaviours and shortfalls of LEMS described in this paper cannot be captured by their approach, as they arise form the higher (but realistic) complexity of the system.

An exploratory approach is proposed in this paper to understand the feasibility of LEMs implemented as sequential markets.

The contributions of this paper can be summarized as follows: First, we uncover the existence of misalignments of objectives in local energy markets when players can trade with the TEC. Secondly, we propose a multi-stage stochastic game to model the interaction of agents through LEMs and with the TEC. Thirdly, we derive a simple but realistic model of prosumers with storage that optimizes her decisions to participate in a LEM. Finally, we identify possible roots of the aforementioned misalignments and we suggest alternatives on how to fix them.

II. PRELIMINARIES

A. Mathematical Model for Players

We begin by introducing a mathematical model for a player that needs to consume energy and has a contract with a TEC.

Let $\mathcal{N} = \{1, \dots, N\}$ be the set of players and $\mathcal{T} = \{1, \dots, T\}$ the set of time-slots. The superscript i will denote variables that correspond to player i and the subscript t will be used to explicit the time-slot.

Each player $i \in \mathcal{N}$ has a fixed demand profile l^i that can be observed every time-slot $l^i = (l^i_1, \dots, l^i_T)$, where l^i_t is the demand of player i at time-slot $t \in \mathcal{T}$. The load profile l^i is the sum of the consumption driven by appliances of player i and the energy generation she might have thanks to a photovoltaic panel (possibly). A positive value of l^i will indicate a net energy consumption and a negative value energy a surplus (due to the renewable generation).

Assumption 1. *We model players with inflexible energy consumption profiles, i.e., all their flexibility is due to energy storage. In our model, the utility of player i is 0 if her required load profile is satisfied or $-\infty$ if it is not, minus payments. Namely, she maximizes her utility when she minimizes how much she is paying for the same energy consumption.*

Players can own batteries. If they do, their capacity will be denoted by $\mathbb{S}^i$ ($\mathbb{S}^i \geq 0$). The maximum energy that the battery can provide in a given time-slot (ramp constraint) will be denoted by $\underline{\delta}^i$ and the maximum energy that the battery can store in a single time-slot by $\overline{\delta}^i$. Furthermore, batteries are not perfectly efficient. We will denote by η^i_c the charging efficiency and by η^i_d the discharging efficiency. The only action that players can take to change their energy consumption profile is to use the battery. That is, players can only decide how much to charge or discharge the battery. We will denote by y^i_t the real amount of energy that enters (positive value of y^i_t) or leaves the battery (negative values of y^i_t) and $\vec{y^i} = (y^i_1, \dots, y^i_T)$.

The feasible set of actions of player i is defined by the set $\mathcal{X}^i = \left\{ \vec{y}^i : 0 \leq \mathbb{S}^i_0 + \sum_{t=1}^{j} y^i_t \leq \mathbb{S}^i,\ \forall j \in \mathcal{T}, y_j \in [\underline{\delta}^i, \overline{\delta}^i] \right\}$

Proposition 1. *The set $\mathcal{X}^i$ is non-empty, closed and convex.*

Proof. It is defined as the intersection of half spaces. □

In this context, the net consumption in time-slot t is given by: $z^i_t = l^i_t + \frac{1}{\eta^i_c} \max\{y^i_t, 0\} - \max\{-y^i_t, 0\}\eta^i_d$ with $y^i \in \mathcal{X}^i$.

The TEC offers player i a buying price β^i_t and a selling price γ^i_t. With the above prices, the utility of player i is given by $u^i(y^i) = \sum_{t=1}^{T} \max\{z^i_t, 0\}\beta^i_t - \max\{-z^i_t, 0\}\gamma^i_t, \quad y^i \in \mathcal{X}^i$.

B. MUDA

In this paper, we use MUDA (Multi Unit Double Auction) [11] as the local market mechanism.

To participate in MUDA, agents can submit a bid for buying or for selling. In both cases, a bid consists of a finite list of quantity-price pairs $B = ((q_1, p_1), (q_2, p_2), \dots, (q_m, p_m))$ with $q_i < q_{i+1}$ and $p_i > p_{i+1}$ ($p_i < p_{i+1}$ for selling). Because MUDA is an auction for divisible goods, when the market clears, players might receive only a fraction of their desired quantity. After all bids have been received, the market mechanism randomly splits all participants into two groups and determines the clearing price [1] for each of the two. MUDA is strategy-proof. To guarantee so, participants trade with the clearing price of the group to which they do not belong. To do so, all the buyers in one side of the market that offered to buy at a price higher than the clearing price of the other side and all the sellers that offered to sell below that price are pre-selected to trade. Because there might be more supply than demand (or vice versa), a rule is used to select which of the pre-selected sellers (or buyers) gets to trade. By doing so, agents cannot influence their trading price.

Furthermore, MUDA is individually rational (agents do not lose money by participating), weakly budget balanced (the market maker does not lose money by running the market and might have a profit) and is efficient only asymptotically in the number of players (as it is impossible to satisfy all described properties at the same time [12]). More details on the mechanism can be found [11].

III. GAME THEORETICAL MODEL

Having introduced a very small example of how a Local Energy market game looks like and a model for a prosumer with a battery, we introduce a formal model.

Consider a setting with $\mathcal{N}$ players and $\mathcal{T} = \{1, 2, \dots, T\}$ stages (or time-slots). Each stage is composed of two steps: a market trading and a final settlement with the traditional electricity company (TEC).

Following the conventions used in game theory, the superscript $-i$ will stand for all players expect player i. The state of player

[1] By finding the intersection of the supply and demand curves.

i (s_t^i) at time-slot t will contain information about the state of charge of the battery and the load of the current and future time-slots of the player. The set $\mathcal{B}_t^i(s_t^i)$ will denote the feasible bids of player i at time-slot t given her state of charge.

Assumption 2. *Players restrict their bids in the market to quantities that they can physically buy or sell.*

In practice, a player that often bids a quantity that she cannot latter provide (or consume) could see her access to the market restricted. Players can be buyers or sellers, but not both in the same time-slot.

After the market clears, player i observes her traded quantity $\tilde{q}_t^i$ and price $\tilde{p}_t^i$ just before the first step finishes. In the second step, she makes sure that her energy demands are satisfied. She can decide to schedule some of her energy needs for later but the rest will have to be bought (or sold) from the TEC. The set of possible settlements with the TEC at time t that player i can offer is given by $\mathcal{G}_t^i \triangleq \mathcal{G}_t^i(s_t^i, \tilde{q}_t^i, \tilde{p}_t^i)$ and depends on the state of the player (how much energy is needed and how flexible that consumption is) and the result of the market. The cost of trading a quantity g_t^i with the TEC at time-slot t is given by $C_t^i(g_t^i)$.

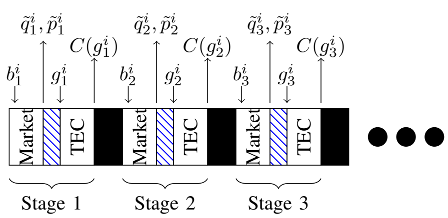

Fig. 1. Timeline of decision process and decision flow for a player in the LEM game

Figure 1 illustrates the decision and information flow for a given player as described above[2].

After implementing an action $g_t^i \in \mathcal{G}_t^i$, player i transitions to the new state $s_{t+1}^i = f_t^i(s_t^i, \tilde{q}_t^i, \tilde{p}_t^i, g_t^i)$ (where f_t^i defines the dynamics of the state transition) and the stage finishes. Denoting by $a_t^i = (b_t^i, g_t^i)$ the pair of actions taken by player i during stage t, where b_t^i is the bid submitted and g_t^i is the quantity traded with the TEC, the set of all such possible actions at the beginning of the stage will be denoted by $\mathcal{A}_t^i$ The set of all possible actions that players other than i can take at stage t is defined as $\mathcal{A}_t^{-i} \triangleq \prod_{j \neq i} \mathcal{A}_t^j$. This set depends on the past actions of all players and their future load profiles.

In a setting with perfect information, player i will have a belief about the likelihood of her opponents playing a given strategy and the equally likely splits of the market into two groups. Let $\Delta\mathcal{A}_t^{-i}$ be the set of probability distributions over $\mathcal{A}_t^{-i} \times W$, where W is the set of all possible 2^{N-1} splits into two groups. Then player's i belief about the possible outcomes of the game at time-slot t is given by $d_t^i \in \Delta\mathcal{A}_t^{-i}$.

Finally, we will denote the expected *Cost-to-go* of player i from stage t onwards while being in state s_t^i as $\mathcal{Q}_t^i(s_t^i)$. In this setting, it is defined as the solution of the two step stochastic optimization problem (1a).

$$\mathcal{Q}_t^i(s_t^i) = \min_{b_t^i \in \mathcal{B}_t^i(s_t^i)} \quad \mathbb{E}_{d_t^i}[A(b_t^i, a_t^{-i}, w, s_t^i)] \tag{1a}$$

where

$$\begin{aligned} A(b_t^i, a_t^{-i}, w, s_t^i) = \min_{g_t^i} \quad & \tilde{p}_t^i \tilde{q}_t^i + C_t^i(g_t^i) + \mathcal{Q}_{t+1}^i(s_{t+1}^i) && \text{(2a)} \\ \text{s.t.} \quad & \tilde{q}_t^i, \tilde{p}_t^i = \mathcal{M}(b_t^i, a_t^{-i}, w), && \text{(2b)} \\ & g_t^i \in \mathcal{G}_t^i(s_t^i, \tilde{q}_t^i, \tilde{p}_t^i), && \text{(2c)} \\ & s_{t+1}^i = f_t^i(s_t^i, \tilde{q}_t^i, \tilde{p}_t^i, g_t^i) && \text{(2d)} \end{aligned}$$

with $\mathcal{Q}_{T+1}^i = 0$. In optimization problem (2a), $\mathcal{M}$ is a function that outputs the results of the market according to MUDA rules, given the bids of all players. Optimization problem (1a) is solved every stage before bidding in the market. We shall assume that if no quantity is traded in the market, it is always possible to buy or sell the required amount of energy with the traditional utility company. As a consequence, the set $\mathcal{G}_t^i(s_t^i, 0, \tilde{p}_t^i)$ is always non-empty. This is a realistic assumption as consumers can always buy all their energy from their utility. The model above defines a multi-stage stochastic game.

Remark 1. *In real implementations of the market, it is possible that players will only be able to observe the result of their trade, but not the bids of other players (privacy is one of those reasons). This would limit the ability of players to reason about the game. In that case, player's beliefs will likely only consider prices and quantities, but not actions.*

IV. A MODEL FOR PROSUMERS PLAYING LEMS

It should not come as a surprise to the reader that the model introduced in the previous section is quite difficult to solve. We do not try to solve such a model in this work. Instead, we search for realistic simulations of it that might exhibit the undesirable effects introduced at the beginning of the paper. To do so, we need to model rational agents in a simple way that is coherent with the game being played and that is able to capture the behaviour in question.

Assumption 3. *We consider agents that reason about the future inasmuch as they schedule their consumption taking into account future prices and that they update their beliefs about the future after observing the results of their actions. We do not model agents that, before deciding on their actions for time-slot t, take into account how those actions will change their environment in future time-slots (only how their state of charge might change).*

We believe that Assumption 3 is realistic and we do not expect implementations of such systems to behave differently.

Remark 2. *Even though the stochastic game as a whole might not be truthful, if as part of a player's strategy, she decides that she wants to buy q units at price at most p during time-slot t, then bidding truthfully in MUDA is the optimal action (in that time-slot).*

[2]We shall use the convention that positive quantities $g^i, \tilde{q}^i$ imply buying energy while negative values are used for selling.

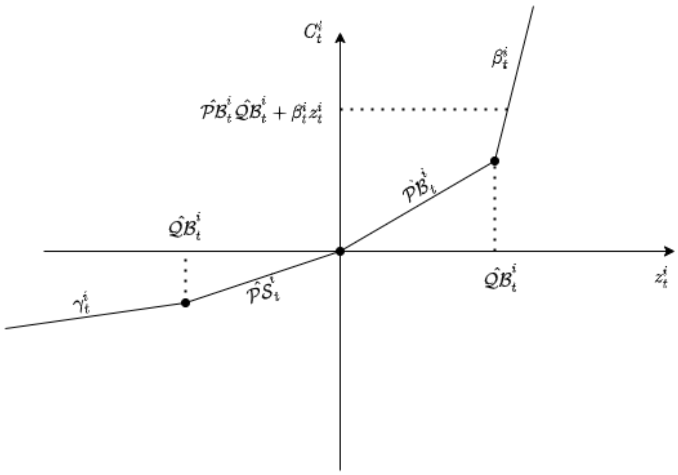

Fig. 2. Graphical representation of the cost function (3).

As a consequence of Assumption 3 and Remark 2, the first-stage optimization problem can be substituted with the optimal amount of energy that each player wishes to consume, given her beliefs about market prices. Indeed, the proposed model is exactly the optimal control of a battery with one addition: for each time-slot, apart from the price of the TEC, there is a market price with an associated maximum tradable quantity. This model extends the model introduced in Section II-A and we will use the same notation.

To keep the model simple, we assume that agents have a probabilistic belief about prices, but to avoid solving a stochastic optimization problem in each step, they use an unbiased estimator of each quantity instead.

As we mentioned earlier, each player has a belief in the form of a probability distribution about each market outcome $\tilde{q}_t^i, \tilde{p}_t^i$. Because players can be either buyers or sellers in the market, they will have a possibly different belief for each case. Let $\mathcal{PB}_t, \mathcal{PS}_t, \mathcal{QB}_t, \mathcal{QS}_t$ be the priors for the buying price, selling price, buying quantity and selling quantities respectively for each time-slot t. The notation $\hat{X}$ will be used to denote an unbiased estimator of X.

For a player i that wishes to buy, the best option is to buy as much as possible in the market (at a better price than the TEC), and acquire the remaining energy with the TEC. The same holds for a player that wishes to sell. Substituting the player's beliefs about quantity and prices of the market in time-slot t, the cost (or profit) of player i during time-slot t associated with a net consumption profile of z_t^i is given by Equation (3) and graphically depicted in Figure 2.

$$F_t^i(z_t^i) = \begin{cases} \hat{\mathcal{PB}}\hat{\mathcal{QB}}_t + \beta_t z_t^i & \text{if } z_t^i > \hat{\mathcal{QB}}_t \\ \hat{\mathcal{PB}} z_t^i & \text{if } \hat{\mathcal{QB}}_t \geq z_t^i \geq 0 \\ \hat{\mathcal{PS}} z_t^i & \text{if } \hat{\mathcal{QS}}_t \leq z_t^i \leq 0 \\ \hat{\mathcal{PS}}\hat{\mathcal{QS}}_t + \gamma_t z_t^i & \text{if } z_t^i < \hat{\mathcal{QS}}_t \end{cases} \quad (3)$$

With the above conventions, the decision problem faced by a player is given by optimization problem (4).

$$\begin{aligned} &\min_{y \in \mathcal{X}^i} \sum_{t=1}^{T} F_t^i(z_t^i) \\ &\text{s.t.: } z_t^i = l_t^i + \frac{max\{y_t, 0\}}{\eta_c} - \max\{-y_t, 0\}\eta_d, \ \forall t \in \mathcal{T} \end{aligned} \quad (4)$$

Because the market is truthful, we find the bid of player i as $b_t^i = (z_t^{i,*}, \hat{\mathcal{PS}}_t)$ if $z_t^{i,*} < 0$ or $b_t^i = (z_t^{i,*}, \hat{\mathcal{PB}}_t)$ otherwise, where $z^{i,*}$ is the value of z in an optimal solution of (4).

Proposition 2. *If the function F_t^i as defined in Equation (3) is convex (which happens as long as $\hat{\mathcal{PB}} \geq \beta \geq \hat{\mathcal{PS}} > \gamma$, for every time-slot), then optimization problem (4) is linear. The ideas of the proof are the same as in [13].*

This is closely related to the setting in [14].

A. Post market

After the market clears, based on the results of the market, players have to decide how much to finally trade with the TEC, if any. To do so, players should modify the cost function (3) by replacing their beliefs about market prices with the real results. Furthermore, if the player managed to trade in the market a quantity $\tilde{q}^i$ then an additional constraint $z_t^i \geq \tilde{q}_t^i$ (if $\tilde{q}_t^i > 0$ or $z_t^i \leq \tilde{q}_t^i$ otherwise), should be added to guarantee that players adhere to their commitments in the market. Here, we assume that players adhere willingly to their commitments with the market, but we could also envision a penalty for deviating from the market.

The value of g_t^i, the quantity to be traded with the TEC is be the difference between the new optimal value of z_t^i and $\tilde{q}_t^i$.

B. Beliefs about the game

As it was mentioned before, we assume that players have a belief (probability distribution) about future market prices and maximum tradable quantities. As these players play the game, they will observe new market's results and they will update their beliefs using the new information, improving their representation of the game.

We model players' beliefs as conjugate distributions and use a Bayesian rule to update them.

In theory, players could have up to $4T$ different beliefs where the 4 is because of the 2 quantities and 2 prices involved. In practice, players will reuse the same belief in time-slots in which they expect them market the behave similarly. For example, because of time-of-day patterns. Each belief will be represented as normal probability distributions with unknown mean but known variance $\mathcal{N}^1(\mu_t^i, \sigma_t)$. Furthermore, each player will have a belief about the value of the mean of such distribution in the form of a normal distribution $\mu_t^i \sim \mathcal{N}^2(\upsilon_t^i, \tau_t^i)$.

After observing n outcomes of the variable of interest over time (which we will assume independent), the new values of υ and τ are given as: $\tau' = (\frac{1}{\tau^2} + \frac{n}{\sigma^2})^{-1}$ and $\upsilon' = \tau'\left(\frac{\upsilon}{\tau^2} + \frac{\sum_1^n x_i}{\sigma^2}\right)$.

If players use a different belief for each time-slot, they will only observe one outcome and that belief will never be used again. In contrast, if players reuse their beliefs across several days, updating them can be useful.

Players can change their beliefs about the game by doing two things. First, by deciding how to map time-slots to distributions (reuse), i.e., two time-slots can use the same distribution and the data of both updates the same prior. Secondly, players can change the initial value of her distribution to reflect their beliefs about the market before observing it.

We proceed to introduce the types of representations used in the rest of the paper. We will denote the number of time-slots in a single day by D.

First we describe three representations: **Optimistic (OPT)**, **Neutral (NEU)** and **Pessimistic (PES)**. The 3 representations map the 4 distributions at each time-slot $t \in \mathcal{T}$ to the 4 representations of time-slot $(t \mod D)$, effectively keeping $4D$ beliefs: one for each quantity and price for each time-slot in day. This exploits the time-of-day effects. Their difference lies in the initial value of v^i. The **OPT** belief assumes that prices in the market are 30% better than the trading with the TEC (both, while buying and selling). The **NEU** belief assumes that prices are only 10% better than the TEC. Finally, **PES** assumes that the prices are the same as the TEC.

We consider two more types of beliefs. One named **Solar (SOL)** and one named **Unique (UNQ)**. The **SOL** tariff considers only two different distributions of each type. Time-slots that occur when the sun should be shining[3] are mapped to a distribution and the rest are mapped to another one. The distribution associated with sun hours is initialized by assuming prices to be 20% better than the market while in the other belief prices are the same as the TEC. At last, the **UNQ** belief considers only 4 distributions, one for each price and quantity. In this case, the prices are considered to be 10% better than those offered by the TEC. Beliefs about quantities are initialized at a large value, stimulating an initial participation in the market.

In addition to different representations, we also consider different frequencies to update beliefs: with every new observation of the market, every n observations of the market or the most extreme case of never updating the belief.

Remark 3. *The **solar** belief described in the previous section is an example of the behaviour that could not have been modeled using the approach in [10]. Under such belief, the players will delay all of their flexible demand until the beginning of the hours in which the sun shines, under the assumption that it will result in a cheaper trade, never consider the possibility of offering that same energy during non-sun hours.*

V. Numerical experiments

At the beginning of this paper we presented an undesirable example of local energy market. In it, players had an incentive to behave in a way that resulted in unnecessary peaks.

In this section, we make use of the model of a prosumer participating in a LEM to replicate the behaviour encountered in the motivating example. Our intention is to understand which characteristics of Example I-A1 can be observed with a large number of players and which of them are only an effect of the size of the example. To do so, we resort to computational simulations of the whole multi-agent system.

[3] $(t \mod D) \in [12, 36]$

Each simulation consists of 9 consecutive days in which prosumers optimize their energy storage and trade using the LEM. Each agent will use the mathematical model described in Section IV. Different simulations will reflect different load profiles and representations of the uncertainty.

Each prosumer owns a battery and some agents have access to solar generation. The demand of each agent is sampled from the Ausgrid dataset [15]. The dataset contains samples every 30 minutes, yielding 48 time-slots ($D = 48$) per day. For each instance of the simulation, the demand of $N = 50$ prosumers is sampled out of the 127 available in the dataset.

Because the generation in the data is not enough to support a LEM (there is little surplus available for trading), for half of the users we generate extra surplus at random. To do so, for each time-slot t in $\{15, \ldots, 30\}$ and each selected agent i, we sample extra generation from a uniform distribution $R_t^i \sim \mathcal{U}[-\frac{3}{10}, 0]$ i.i.d such that the new demand is given by $l'_t = l_t + R_t$.

The battery characteristics are the same for each prosumer: $\mathbb{S} = 13$, $\overline{\delta} = -\underline{\delta} = 5$, $\eta_c = \eta_d = 0.95$.

Two price tariffs are used for our simulations: a flat rate and a time-of-use tariff. In the flat rate, the price of buying energy is constant with a value of 30. The time-of-use tariff consists of two periods: a cheap one and an expensive one. The first one spans the first 32 time-slots of every day and has a value of 20 while the latter spans the remaining time-slots of every day and has a value of 30. Both tariffs have the same price for selling for all time-slots: 10. All prices are in cents per kilo watt hour.

In this paper, players use a rolling horizon of length 48 time-slots (or 1 day) to solve the optimization problem (4). Participants only implement the first decision out of the 48 that they obtain before moving to the next time-slot.

To solve optimization problem (4), prosumers need to know their load in the next day (because of the rolling horizon procedure). Players have perfect knowledge of their load in the first of the 48 time-slots, and use a forecast for the remaining 47. We adopt the **AvgPast** forecast as described in [16] as it has been shown to provide a good performance for the operation of storage without being too complex.

All market mechanisms will be run using the auction mechanism MUDA as implemented in PyMarket [17] and the optimization problems involved in controlling the battery are solved in CPLEX. Simulations were run in parallel using GNU parallel [18].

In all our simulations, players learn from their own experience. That is, they update their belief based solely on the market prices and quantities they have been subject to, but not those of the other players. A player will update her beliefs about prices only if she gets to trade.

We conclude this section with the four metrics of interest studied in this paper. First, we looked at the **Social Cost (SC)**, the sum of the cost incurred by all players during all time-slots. This is an indicator of how well the market performs from the perspective of the players. Secondly, we look at two statistics, the maximum peak and the most negative peak of the aggregated net consumption profiles. We refer to them as **max** and **min** respectively. Finally, we look at the total amount of energy that gets matched locally **(LM)**. This is an upper bound of the energy traded in the market since all the energy traded in the market gets matched locally, but it is possible for two prosumers to consume and inject at the same time without having traded. Because all of the above metrics are difficult to contextualize on their own, instead of presenting the corresponding value, we will always show the relative change of the metric with respect to the scenario without a market in which players optimize their battery independently of each other.

A. Results and Discussion

We begin our presentation of the results obtained by directing the attention of the reader to Table I.

TABLE I
STATISTICS OBTAIN WITH DIFFERENT CONFIGURATIONS.

Tariff	Freq	Belief	SC	min	max	LM	net LM
Flat	0	SOL	-11	6	95	62	396
TOU	1	NEU	-2	-54	57	-36	187
		OPT	1	-150	-40	-3	284
		PES	-1	0	40	-6	282
		SOL	-1	-7	7	-3	285
		UNQ	-1	-6	-7	13	337
	0	PES	0	0	0	0	297
		SOL	-11	-155	-1	50	435

In it, the average relative change with respect to the scenario without a market is presented. For **SC**, a negative value indicates that the market managed to decrease the total cost (a positive outcome). For both **min** and **max**, a negative value is desirable as it denotes that the maximum positive peak or the maximum negative peak were reduced. Finally, a higher and positive value of the locally matched energy **LM** is beneficial as this was one of the motivations to introduce energy markets.

In Table I, the column Freq denotes the number of samples collected before updating the beliefs. In addition to not updating their beliefs, in simulations with a Freq value of 0, players did not trade in the market, they only used the belief to change their battery schedule planning. *Solar Tariff* as used in the legend of Figures 3 and 5 refers to the **SOL** belief in the Freq 0 scenario. The last column of the table shows the total amount of energy (in kWh) that got traded locally during the simulation. We can observe that the *Solar Tariff* is less effective when paired with a Flat tariff.

In Figures 3 and 5, each curve represents the difference between the aggregated net load of a simulation using the market and a set of beliefs and the aggregated load obtained without a market (for the same parameters). The x-axis coincides with the default aggregated load. In Figure 3 players are subject to a Time-of-Use tariff, while in 5 they use a Flat tariff.

By turning our attention to Figure 3 we notice two things. First, of all the beliefs plotted in red, most of them produce small deviations with respect of the default operation (close to 0) while one of them creates very high peaks. The belief producing the peaks in red is **NEU**. Interestingly, Table I indicates that for a ToU tariff, the **NEU** achieved a reduction in the social cost, while creating higher peaks and reducing the amount of energy locally matched. Indeed, we observe a misalignment of objectives. To explain why this behaviour emerges, we refer the reader to Figure 4. In it, we plotted the same curve producing the peaks of Figure 3 in blue. In red, we plotted the total amount of energy that participants asked in the market at the beginning of each time-slot. We observe that there is a mismatch between the two quantities. Moreover, players try to trade in the market until the change in price. At that point, they decide to buy all their required quantity. This is a consequence of the expected market price in the most expensive period: $30 * 0.9 = 27 > 20$, the default low TOU price. We argue that this type of behaviour, only due to the beliefs of a player, can show up in real deployments of LEMs with dire consequences. Unfortunately, from an economic perspective, this behaviour is rational for agents as it allows them to delay their expenditure [19].

One might wonder why we do not see the same effect observed for **NEU** for **OPT** if we still have that $30 \times 0.7 = 21 > 20$. This is because the actual price of electricity is related to the round-trip efficiency of the battery. In this case, with a round-trip efficiency of 0.95^2, the actual cost of charging during the low period and discharging in the most expensive period is $20/0.95^2 \sim 22.16 > 21$. This explains why players do not engage in the frenetic behaviour of consuming pre-peak: they still believe that trading in the market during the most expensive period will be cheaper.

The second thing to notice in Figure 3 is that the *Solar Tariff* that performs fairly well, performs quite badly when the default tariff is flat. This is important to notice as it reveals that a belief is not bad on itself, but only inasmuch as it is coupled with a default electricity tariff.

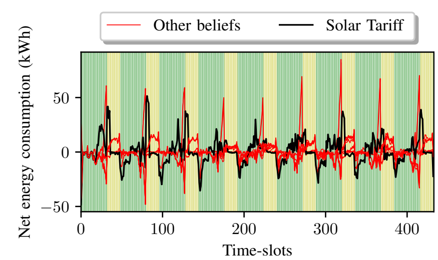

Fig. 3. All net profiles obtained by using different beliefs in one simulation with a ToU rate.

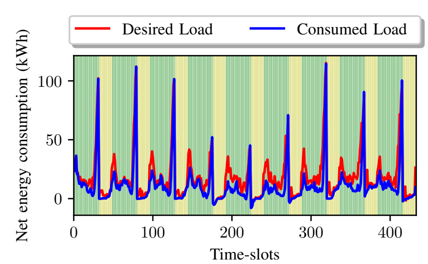

Fig. 4. Net load asked in the market versus the net load actually consumed.

Our numerical findings support the hypothesis formulated around the example in Section I-A. When players have access to an unlimited supply of energy outside the market, the tariff at which that energy can be bought should be carefully designed. Otherwise, it is possible that players (inadvertently) game the

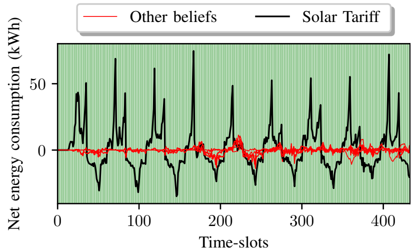

Fig. 5. All net profiles obtained by using different beliefs in one simulation with a flat rate.

system, trying to increase their profits at the cost of the physical grid.

Flat rates offer less incentives than ToUs to change the patterns of consumption in ways that result in spikes, for most of the beliefs tested in this paper. Nevertheless, they offer slightly less efficient environments. It is not unthinkable to imagine a trial in which the flat rate is replaced with incentives in special times of the day to increase local consumption. Such incentives should be designed carefully, as we showed that they could prove dangerous to the operation of the power grid.

VI. Conclusions

Local Energy Markets are increasingly being proposed as a solution for distributed energy resource management on smart distribution grids. Nevertheless, several aspects of such programs related to their implementations and how they will alter the behaviour of their participants remains unknown and further analysis is required to understand all possible ramifications.

In this paper we formalize the notion of a local energy market with a secondary supplier and we study the effect of players' beliefs in the net aggregated load of the system. Simple pathological examples in which the equilibrium strategies produce undesirable peaks for the grid operator were presented. A decision model for prosumers participating in LEMs was developed and used to reproduce the pathological behaviour in numerical simulations with realistic data.

Our experiments indicate that some strategies and beliefs of players can create peaks of consumption that would not exist without the market. Flat tariffs seem to be better adapted to be coupled with local energy markets, even though they provide lower energy matching capabilities.

Local energy markets will require the design of new mechanisms capable of dealing with existing tariffs or new tariffs capable of supporting markets while still providing efficient outcomes.

Looking at the results obtained in the paper we notice that some of the problems seem to arise from players "waiting" for better deals. A mechanism that clears day-ahead could provide the players with additional information to better schedule their load. Some possible examples include [8], [20], [21].

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