Integration of Load Shifting and Storage to Reduce Gray Energy Demand

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Abstract: The smart grid concept offers an opportunity to design new environmentally friendly energy markets for reducing CO2 emissions. To achieve this goal, we should increase the use and penetration of green energy while softening our dependency on gray (non-environmentally friendly) energy too. In this work we show how load shifting and storage can be incorporated into new energy markets to reduce gray energy consumption. We used multi-agent-based simulations that are fed with real data to analyze the influence of load shifting and storage to reduce gray energy demand as well as the behaviour of prices for gray and green energy. Results suggest that reduction in gray energy consumption is feasible during peak times, i.e. up to 15%. Nonetheless, if the amount of renewable resources is increased 50%, higher reductions can be achieved, i.e. up to 30%. Furthermore, one of the findings also suggests that storage helps to keep the price of green energy low.

1 INTRODUCTION

Engineering smart grids is a challenging task that must deal with new emerging actors, e.g. prosumers [1] as well as with complex interactions between people, technology and natural systems (Schuler, 2010; Ramchurn et al., 2012). Among those interactions, economic and power flows are of utmost importance (van Werven and Scheepers, 2005; Schuler, 2010).

Novel mechanisms have been already proposed to not only optimize economic and power flows but also improve the integration of renewable resources (Ilic et al., 2012; Kok et al., 2005; Capodieci et al., 2011; Mihaylov et al., 2014). Nonetheless, they have not analyzed the potential use of load shifting and storage to reduce gray energy demand and improve the integration of renewable sources.

As a way to analyze such potential use, we take NRG-X-Change as an example of a novel mechanism that can benefit from load shifting and storage. NRG-X-Change aims at promoting the trade and flow of locally produced green energy within dwellings (Mihaylov et al., 2014). It offers to prosumers the possibility to trade their excess of green energy by using NRGcoins, which are virtual coins inspired by the Bitcoin protocol (Nakamoto, 2008). Unlike Bitcoins, NRGcoins are generated by injecting green energy into the grid rather than using/spendig computational power (Mihaylov et al., 2014).

Although NRG-X-Change promotes the local trade and consumption of green energy between residential consumers and prosumers, it does not guarantee that green energy production fully matches consumption. In fact, when green energy is not enough to cover demand, consumers and prosumers will consume gray (non-environmentally friendly) energy to satisfy theirs needs and maintain a given level of comfort. To soften the dependency on gray energy, i.e. reducing its consumption, load shifting and storage capabilities can be integrated into NRG-X-Change. In this way, "original gray consumption" can be covered using stored green energy or delayed until green energy becomes available. Nonetheless, this integration is far from trivial, since it has been already shown that such capabilities impact energy demand and price (Prüggler et al., 2011), which may potentially inhibit trade and/or increase consumption.

In this work, we present preliminary results on the integration of load shifting and storage capabilities into NRG-X-Change. Using real consumption and production data provided by a Belgian retailer, we performed numerical simulations to analyze the performance of storage and load shifting as well as the impact on energy prices and the reduction of gray

[1]The term prosumer refers to energy consumers that can also produce their own power.

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energy consumption. Our simulations are based on a multi-agent system that replicates the behaviour of main stakeholders, i.e. energy retailers, consumers and prosumers.

Results suggest that load shifting and storage can reduce energy demand during *peak hours*. In this way, a 15% reduction can be achieved within a typical Belgian district that is on average composed of 60 households in which 10% are prosumers. Nonetheless, as our results indicate, 30% reduction can be achieved during peak hours if the number of prosumers reaches 50% within the Belgian market, which is a plausible scenario for the comming years (Rickerson et al., 2014).

Furthermore, another finding suggests that storage plays an important role to keep green energy prices low as prosumers can inject and trade energy from batteries, which provides a more constant supply of green energy.

The rest of the paper is organized as follows. Section 2 presents related work covering aspects such as load shifting, demand response and negotiation strategies for energy markets. Later on, Section 3 describes green and gray energy markets as well as load shifting and storage capabilities. Afterwards, Section 4 shows preliminary results, whereas general conclusions and future work are presented in Section 5.

2 RELATED WORK

2.1 Modifying Energy Consumption

Different strategies can be applied to modify the consumption of energy. On the one hand, storage capabilities can reduce demand for energy during critical periods by using green energy that has been previously stored when green energy was abundant (Prüggler et al., 2011). On the other hand, demand response (DR) capabilities can be used to reduce customers' normal consumption pattern by shifting a percentage of their demand to off-peak hours (Gottwalt et al., 2011; Aghaei and Alizadeh, 2013). Different techniques have been applied to support DR capabilities, which can be roughly classified into three schemes: 1) Price based: in this scheme the price of energy changes over time, which may motivate customers to also change their consumption profile. 2) Incentive or event-based: customers are rewarded for changing their energy demand upon retailer's requests. 3) Demand reduction bids: customers send demand reduction bids to energy retailers (Siano, 2014).

Although several DR techniques and programs have been proposed in literature (Aghaei and Alizadeh, 2013; Siano, 2014) and implemented in pilots (Niesten and Alkemade, 2016) respectively, they all agree on an important issue: residential customers offer a lower potential for demand reduction compared to commercial and industrial consumers (Gottwalt et al., 2011; Aghaei and Alizadeh, 2013). Likewise, in (Gottwalt et al., 2011; Prüggler, 2013), it is also reported that the economic benefits are moderate for residential consumers compared to the required investment. Consequently, as an attempt to better reduce residential demand for gray energy, we aim at enhancing DR techniques by using storage capabilities. This combination will allow not only to shift energy demand to time slots in which green energy is produced but also to slots in which storage devices discharge green energy to be consumed.

2.2 Negotiation Strategies

Several mechanisms have been also proposed to trade energy within smart grids. Nobel (Ilic et al., 2012) applies a market mechanism in which prosumers offer their excess of energy by submitting asks (sell orders) while consumers submit bids (buy orders). They, both prosumers and consumers, submit asks and bids based on predictions about their expected production and consumption respectively. Later on, asks and bids are matched based on price, i.e. a scalar value. Likewise, PowerMatcher (Kok et al., 2005) uses a market mechanism for matching supply to demand. Nonetheless, bids and asks are not scalar values but price curves. An aggregator is in charge of grouping individual curves so that more supply and demand can be matched. The orderbook then computes price equilibrium to match aggregated asks and bids.

In (Capodieci et al., 2011), the authors propose a mechanism in which energy is contracted by individual consumers and prosumers via negotiations. Although no central mechanism rules the price of energy, the energy retailer is in charge of assigning prosumer-consumer pairs for negotiation. In a similar vein, Wang and Wang have proposed adaptive negotiation strategies to trade energy between smart buildings and grid operators (Wang and Wang, 2013). The trade takes the form of a bi-direcctional process in which a seller, e.g. grid operator, continuously adapts (submits) prices for energy (asks), while a buyer replies with counter offers (bids). Bids and asks can be adapted using the Adaptive Attitude Bidding Strategy (AABS) or an improved version that applies particle swarm optimization techniques (PSO-AABS).

Similar to Nobel and PowerMatcher, NRG-X-Change presents a market mechanism to locally trade energy between consumers and prosumers (Mihaylov et al., 2014). It relies on prosumers injecting their excess of green energy into the grid and trading NRGcoins, which are used to pay for green energy. In this way, prosumers injecting green energy are rewarded with NRGcoins, whereas consumers must pay for the usage with NRGcoins (Mihaylov et al., 2014).

To trade NRGcoins, consumers and prosumers participate in a continuous double auction (CDA) (Shoham and Leyton-Brown, 2008), where buyers and sellers apply bidding strategies to submit bids and asks respectively. NRG-X-Change originally uses the so-called adaptive attitude (AA) strategy, which relies on short-term and long-term attitudes for *adapting* to market changes (Ma and Leung, 2007; Mihaylov et al., 2015). Briefly, a short-term attitude encourages the agent to be eager for more profit, i.e. selling at high prices or buying at low prices, while a long-term attitude encourages the agent to be eager for more transactions, i.e. submitting low asks or high bids. Based on market events (transactions, 'atractive' bids and asks), AA continuously updates an agent's eagerness to sell or buy items.

In this work, we use the NRG-X-Change to trade green energy as it offers a novel mechanism that incentives prosumers to inject their excess of green energy while promoting a transparent economic exchange via NRGcoins. To trade gray energy, however, we apply a negotiation approach based on AABS as this type of negotiation mimics retailer's control on gray energy prices, i.e. they establish prices based on their private reservation price. The next section elaborates on these issues as well as on the overall architecture to support load shifting and storage.

3 ENERGY TRADE

Briefly, the electricity system (ES) is composed of all systems and actors involved in production, transportation, distribution and trade of electricity. This ES can be divided into a commodity subsystem and a physical subsystem (van Werven and Scheepers, 2005). The former covers all economic flows resulting from electricity trade, whereas the physical subsystem consists of all equipment that produces, transports and uses the electricity.

In our case, as part of the commodity subsystem, we assume the existence of green and gray energy markets, which operate in parallel but use different mechanisms. Moreover, the physical subsystem specifies the overall smart grid architecture as well as the way storage and load shifting operate.

3.1 Commodity Subsystem

3.1.1 Green Energy Market

We use the NRG-X-Change approach to allow the flow and trade of green (solar) energy between prosumers (Mihaylov et al., 2014). We assume consumers and prosumers are connected to the electricity grid via a substation (see also Sect. 3.2). Excess of locally produced green energy is fed into the grid and is withdrawn mostly by consumers. The billing is performed in real-time by the substation using NRGcoins, which are independently traded on an open currency exchange market for their monetary equivalent.

NRGcoin is a virtual coin inspired by Bitcoin whose main advantage is that it can be exchanged for a specific quantity of green energy at any time. For instance, if a prosumer injects 10 kWh right now, (s)he will earn NRGcoins accounting for that amount of energy, based on the local supply and demand measured by the substation (Mihaylov et al., 2014). Later on, e.g. after few years, regardless of the NRGcoin market value, the prosumer can use the same NRGcoins to pay 10 kWh of green energy under similar energy supply and demand conditions as during injection (Mihaylov et al., 2014).

Unlike the original NRG-X-Change, to trade NRGcoins, we use the Adaptive-Aggressiveness (AAggressive) bidding strategy as it applies a learning approach, which has been shown to be very robust in dynamic markets (Vytelingum et al., 2008). AAggressive is composed of four basic blocks: *equilibrium estimator*, *aggressiveness model*, *adaptive layer* and *bidding layer* (Vytelingum et al., 2008). Based on historical record of prices, the equilibrium estimator computes the target price for the trader, whereas the aggressiveness model determines the trader's risky behaviour to submit high (low) bids (asks). The adaptive layer implements short-term and long-term *learning* to adapt the behaviour of the trader. While the short-term learning updates the agent's aggressiveness, the long-term learning modifies the agent's bidding behaviour. Finally, the bidding layer implements a set of rules to determine whether the trader must submit bids(asks) or not.

Parameter tuning for AAggressive is done as suggested in (Vytelingum et al., 2008). Nonetheless, we specified constraints for bids and limit prices. On the one hand, minimum and maximum allowed bids in the market are as follows. The minimum bid is 0.01 Euro, while the maximum bid is 0.215 Euro, which is the estimated average price for residential customers in Belgium during 2014 (VEA, 2014). On the other hand, limit prices for buyers and sellers were randomly defined in the range 0.01 and 0.215 Euro.

3.1.2 Gray Energy Market

In (Mihaylov et al., 2014), the authors allow prosumers trading green and gray energy with NRGcoins. In this work, however, to trade gray energy prosumers must pay in Euro. The main motivation is that NRGcoins should be perceived as assets that guarantee provision of green energy only. Similar ideas have been previously explored. For instance, ecolabels that inform customers on whether some products and services are green or eco-friendly (Room and Institute, 2010).

Since prosumers and consumers must consume gray energy whenever there is a lack of green energy, prosumers and consumers use the AABS strategy to negotiate prices for gray energy with the substation (Wang and Wang, 2013). As described in Section 2.2, the AABS strategy relies on a bi-direcctional negotiation in which a buyer (prosumer/consumer) submits bids (price willing to pay for energy) to a seller (substation) that responds with asks (desired selling prices). Once the buyer's bid is equal to or greater than the seller's ask, an agreement has been reached to trade energy among the two of them. The final price for energy is the average between the bid and the ask.

Substation decreases or increases their asks depending on AABS selling strategy and the availability of green energy. If green energy supply is bigger than demand, the price for gray energy goes down, otherwise it goes up. The idea is to discourage consumers and prosumers of using gray energy. This way, if gray energy price is higher than their reservation price, they will try to shift loads. Nonetheless, even if the price is high and green energy is not available, they will have to use gray energy anyway.

To decrease or increase gray energy prices, the AABS' L_2 parameter (Wang and Wang, 2013), which is used to modify the substation's reservation price, is continuously adapted using Equation 1.

$$L_2 = \begin{cases} L_2 - \alpha \times (GS/PwD) & \text{if } GS > PwD \\ L_2 + \alpha \times (GS/PwD) & \text{otherwise} \end{cases} \tag{1}$$

where GS is the supply of green energy, PwD is the power demand and α is a random value between 0.001 and 0.005. The reservation price of the substation is initially fixed at 0.2 Euro, which changes depending on $L2$ and is a bit lower than the maximum price for green energy (see Section 3.1.1). Reservation prices for consumers and prosumers are randomly determined between 0.15 and 0.30 Euro. The rest of AABS parameters are tuned as suggested in (Wang and Wang, 2013).

3.2 Physical Subsystem

3.2.1 Overall Architecture

In this work we use real-world data that has been provided by a Belgian energy retailer. The physical setting contains prosumers that are equipped with solar panels, which allows them to generate their own power. Both, consumers and prosumers have smart meters that report to the substation the amount of energy being absorbed from and injected to the grid. As meters only report the injected energy after prosumers satisfied their own demand, we do not have a full picture of the actual energy being produced. The same applies for the absorbed energy that is reported to the substation, i.e. we do not have information about the overall energy being consumed by prosumers as part of it is satisfied with their solar panels. Consequently, we do not have information about prosumers' internal energy consumption and production but only about energy flows between the meters and the substation. Furthermore, the measurements take place every 15 minutes, which are standard time slots in the electricity system (Bush, 2014).

3.2.2 Storage

In our setting we assume prosumers are the only ones using batteries since they can generate their own energy and store their excess after satisfying own consumption. Although commercial batteries offer storage capabilities in the range of 4 to 13 kWh, we randomly assign prosumers storage in the range of 4 to 7 kWh. E.g. Tesla's powerwall offers storage of 7 and 10 kWh (Tesla, 2016), whereas Bosch's offers storage of 4.4 and 13.2 kWh (Bosch, 2016) respectively. Moreover, to the best of our knowledge, only small capacities per prosumer have been properly tested and installed within current pilots. E.g. within the project Grid4EU, home batteries with 4kWh capacity have been already installed in the French region of Carros (Grid4eu, 2016). Regardless of the capacity of the battery, we assume they have an efficiency of 90%, for both charge and discharge, which is a lower bound to the efficiency already provided by commercial batteries. E.g. Tesla and Bosch respectively report 93% and 97.7% efficiency for storage solutions that also include power inverters (Tesla, 2016; Bosch, 2016).

3.2.3 Load Shifting

As previously reported in (Mert et al., 2008), loads associated to devices such as washing machines, dish washers, tumble dryers and air conditioners might be "easily" shiftted since they not only account for 20% to 30% of the overall consumption (Paatero and Lund, 2006) but also presented the highest willingness to postpone start according to residential customers (Mert et al., 2008). In this way, when green energy is not available, we assume 20% to 30% of consumers' and prosumers' loads can be shifted to reduce consumption of gray energy. Although loads can be shifted to time slots in which green energy is abundant, loads cannot be shifted for an unlimited amount of time. Realistic times to postpone the start of loads are between 30 min to 3 hours, i.e. 2 to 12 slots, as reported in (Mert et al., 2008).

Likewise, we also assume a waiting time before a consumer/prosumer can delay another load again. We randomly assign waiting times to consumers and prosumers in the range of 48 and 96 slots, which means that they will have to wait at least half day before delaying another load. Furthermore, since consumers and prosumers could all try to shift loads at the same time, we need to avoid such case too as it may generate demand peaks at a further stage, e.g. when their time slots expire and they need to re-start loads. To this aim, whenever a consumer or prosumer wants to start the shift of a load, (s)he can only do it with a probability of 0.5. If probability is in her/his favour at that time slot, (s)he can start shifting the load, otherwise (s)he will have to try again in the next time slot. In this way, we aim at constraining the start of load shifting as well as at spreading controllable devices' loads through a full day.

Finally, to allow load shifting, consumers and prosumers use a "set and forget" approach in which they pre-set the loads that can be shifted (e.g. washing machines, dish washers or tumble dryers) as well as the time they can be delayed, i.e. a number between 2 and 12 slots. In addition, as load shifting depends on whether green energy is available or not, we assume that information about availability could be potentially delivered via internet, sms, or display directly on the appliance (Mert et al., 2008).

4 PRELIMINARY RESULTS

4.1 Simulation Settings

To understand the impact of load shifting and storage for gray energy demand reduction and energy trade, we use a multi-agent system that is modeled and implemented in Repast simphony (North et al., 2013). The multi-agent system is fed with real consumption and production data provided by a Belgian energy retailer. In our simulations, consequently, we use a week of real consumption and production of electricity within a typical Belgian district, which is composed of 54 consumers and six prosumers equipped with solar panels and batteries. Storage capacity for batteries is randomly assigned between 4 and 7 kWh. Finally, due to the plausible increase of prosumers within the electricity system, and as an attempt to understand future scenarios, we also present results for settings containing higher percentage of prosumers (Rickerson et al., 2014).

4.2 Energy Consumption

In this section we present plots of the average amount of gray and green energy being consumed by both prosumers and consumers. We show values for a typical Belgian district, i.e. prosumers account for 10% of households, as well as for futuristic/plausible settings in which the percentage of prosumers are respectively 30% and 50%. To achieve these percentages, we fed real consumption and production data of 18 and 30 prosumers respectively in our simulations. These numbers represent the 30% and 50% of households in a typical Belgian district (usually composed of 60 households).

Figure 1 shows the average consumption of green energy for different percentage of prosumers for a whole week. As one can see, the more prosumers, the more green energy being consumed. Although main consumption occurs at daytime hours, when prosumers inject their excess of production after covering their own demand, consumption of green energy can also be observed at night time thanks to storage. For instance, as seen in Figure 1, green energy consumption is observed during night hours between the first and second day.

In the same vein, Figure 2 depicts the average consumption of gray energy, which shows that the more prosumers, the less gray energy is demanded during daytime hours. Unlike, green energy consumption, gray energy consumption occurs mostly at late afternoon and early morning, when green energy is not generated. Consequently, it is extremely important to reduce the overall energy consumption during those periods as prosumers and consumers will mostly use gray energy.

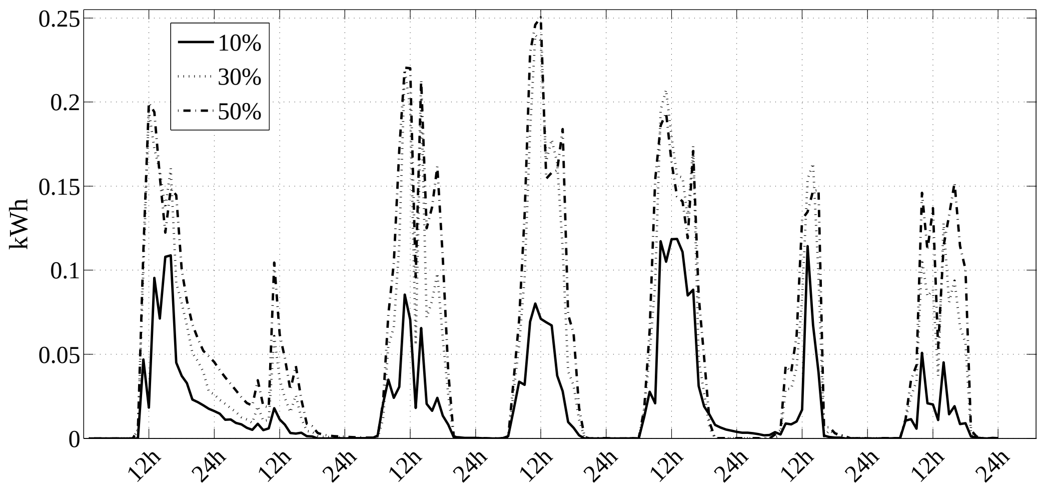

Figure 1: Average consumption of green energy per household for different percentage of prosumers in a district. Note that green energy can also be consumed at night time thanks to storage and load shifting.

4.3 Consumption Reduction

In order to determine whether reduction in consumption can be achieved using load shifting and storage, we have analyzed the overall consumption, i.e. green and gray consumption, of a typical Belgian district for a whole week. We measured the average energy consumption when neither load shifting nor storage are available (original consumption) as well as the case when both are available (adapted consumption). Figure 3 shows both measures, original (dashed line) and adapted (solid line) consumption, which represent the average demand the susbtation is expected to face. Moreover, it also shows the average reduction being achieved (dotted line).

Although peak reduction can be achieved for some days, such reduction is moderate as the highest reduction is around 0.05 kWh, which is approximately a 15% reduction compared to the original consumption. Nonetheless, most of the peak reduction takes place at night time, when green energy is not generated, which implies that demand for gray energy will most likely decrease.

As we also wanted to determine whether a higher reduction can be achieved for future settings, we increased the percentage of prosumers per district. Figure 4 shows the average reduction in districts containing 10%, 30% and 50% of prosumers. The highest peak reduction is achieved by the district with 50% prosumers and is above 0.12 kWh, which represents a reduction of at least 30% compared to the original consumption. Nonetheless, one must be aware that such reduction is only possible by providing consumers and prosumers with load shifting capabilities as well as providing storage capabilities to prosumers. The performance of both capabilities is described in the following sections, i.e. Sections 4.4 and 4.5.

4.4 Storage

To determine how much green energy can be stored after prosumers cover their own needs, we measure the average state of charge (SOC), which indicates the percentage of occupancy of prosumers' batteries, i.e. how full batteries are, where 0% = empty and 100% = full. Figure 5 shows the average SOC per prosumer. It depicts three lines, one per each setting, i.e. districts containing 10%, 30% and 50% of prosumers. Batteries have capacities among $4\,kWh$ and $7\,kWh$.

As it can be observed, batteries constantly charge and discharge their energy to meet energy demand. Discharge usually starts around late afternoon (the hours when green energy production decreases), whereas charge starts before noon. Furthermore, discharge provides green energy to be consumed at night time as observed in Figure 1.

Batteries, however, only reach full charge during the first day. This aspect should be considered before installing batteries with big capacity as they may not always be filled, which means a waste of storage capacity. Likewise, two more findings should also be considered. First of all, load shifting could help to fill batteries as initial consumption can be delayed (see Figure 6), which may give time to store green energy as seen during the first day in Figure 5. The second finding is related to the drop of production during the second day. Drops in production will not allow batter-

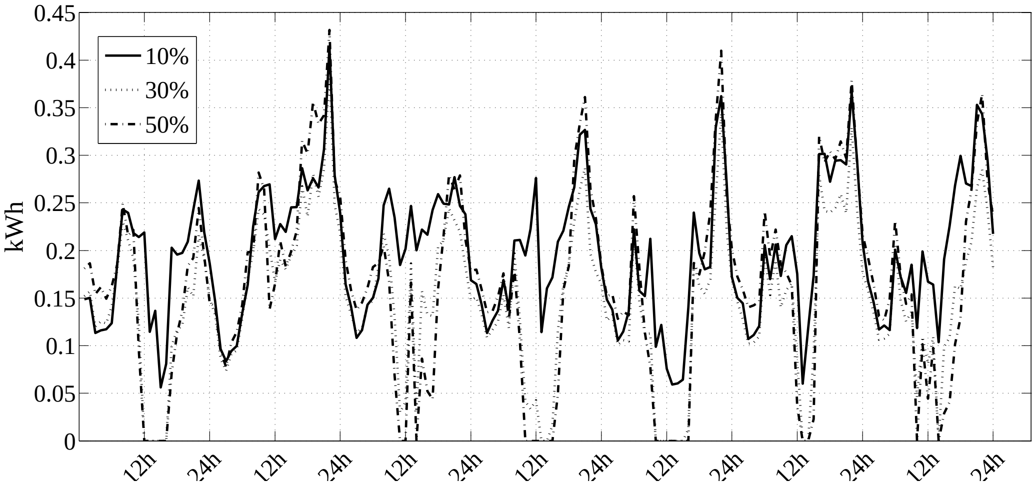

Figure 2: Average consumption of gray energy per household for different percentage of prosumers in a district using storage and load shifting. Note that when the percentage of prosumers is above 30%, consumption of gray energy reduces considerably during daylight hours.

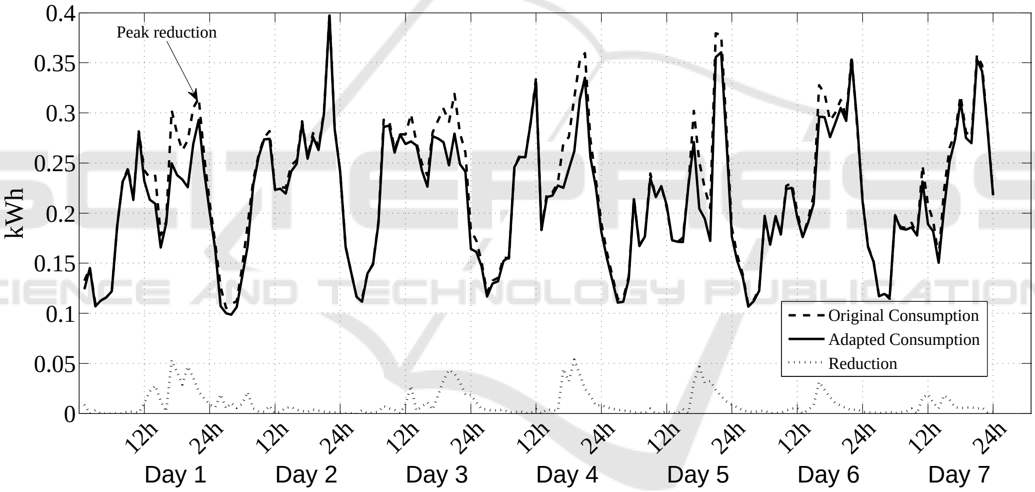

Figure 3: Average values for original and adapted consumption (storage and load shifting capabilities) per household in a typical Belgian district with 10% prosumers. The dotted line represents the average reduction in consumption per household.

ies to be completely filled as they will have to provide green energy at night time. Moreover, since green energy is also scarce due to production drops, more loads would be shifted, which forces batteries to provide energy when the associated time slots expire.

In this way, as load shifting directly impacts on the charge and discharge of batteries, an optimal planning of storage capacity that takes into account load shifting is also required. Such planning will allow to efficiently use storage (i.e. no waste of capacity) and provide more flexibility for load shifting. Nonetheless, it is clear that storage helps to meet both original and shifted demands. The performance of load shifting is presented in the next section.

4.5 Load Shiftting

Although load shifting aims at curtailing energy demand by delaying the start of controllable devices (e.g. washing machines, dish washers and tumble dryers), the delay cannot last for more than three hours, i.e. up to 12 time slots (Mert et al., 2008). In this way, our mechanism allows to shift chunks of energy consumption whose dimensions are time and power (watts). Shifted chunks have a time length of 2 to 12 time slots and a power given by the amount of demand being curtailed (i.e. 20% to 30% of the overall consumption). When the chunks of all consumers and prosumers are aggregated, they can provide a consid-

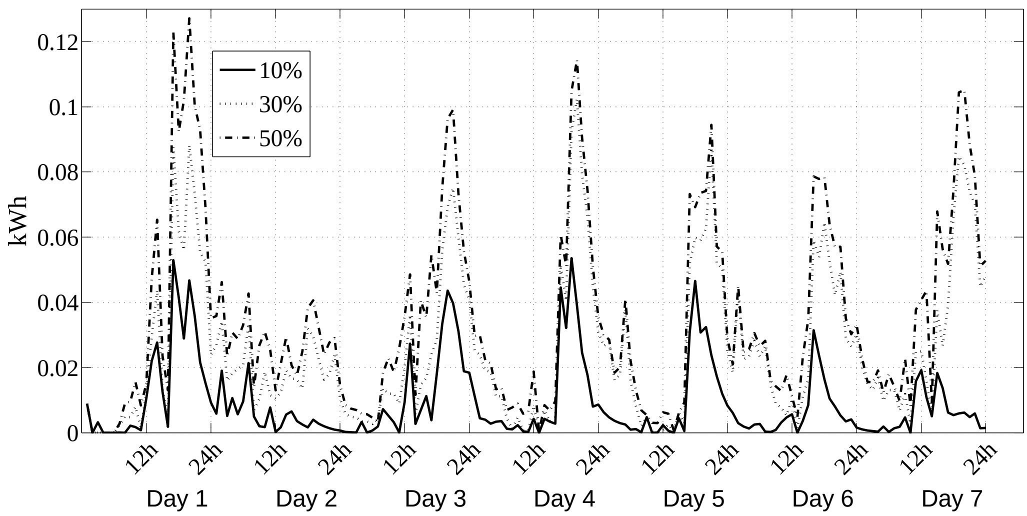

Figure 4: Average reduction in consumption per household using storage and load shifting capabilities for different percentage of prosumers.

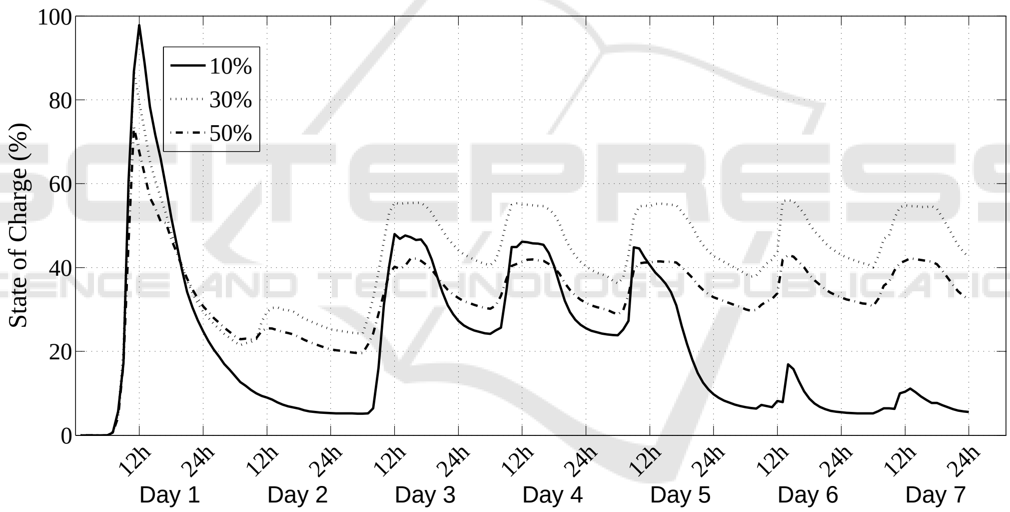

Figure 5: Batteries' average state of charge (SOC) per prosumer for different percentage of prosumers. 0% = empty and 100% = full.

erable amount of curtailment per slot as depicted in Figure 6.

Figure 6 shows the total demand being curtailed per time slot for three districts composed of 10%, 30% and 50% prosumers respectively. The highest amount of curtailment is observed in districts with low percentage of prosumers, i.e. 10% and 30%. The reason is that since green energy is scarce, i.e. prices for green and gray energy go up (see also Section 4.6), consumers and prosumers try to shift more loads. Furthermore, as can be seen, it is possible to curtail up to $2\,kWh$ within a single time slot, e.g. before third day's noon.

Finally, regardless of the amount of demand being delayed, a shifted load is always re-started either when green energy becomes available or before the end of its time slot, so they are never delayed more than three hours (12 time slots).

4.6 Price History

As not only energy-related measures are important to understand smart grids, but also economic aspects, we have also analyzed the price behaviour of both green and gray energy. The analysis of energy prices provides an idea about the expected profits or losses in a

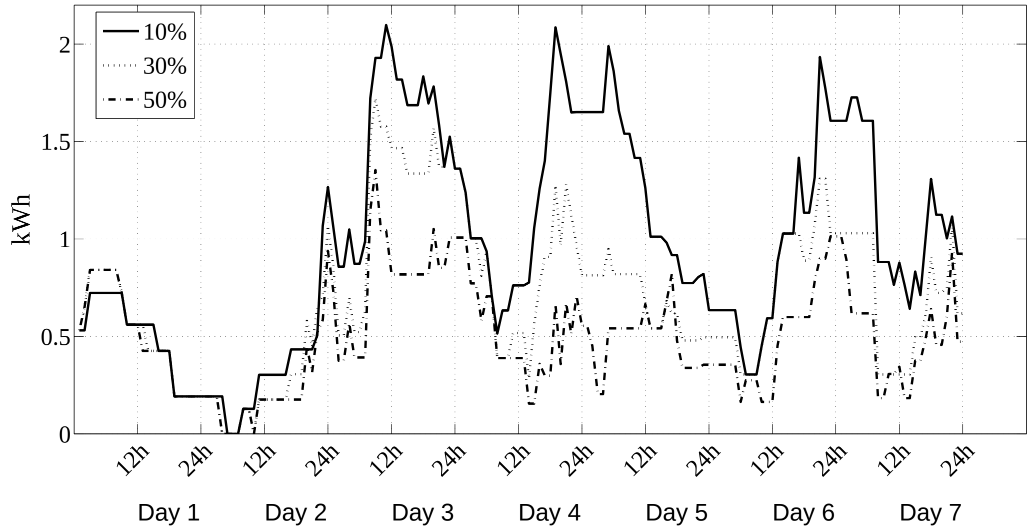

Figure 6: Total demand being curtailed per slot over seven days.

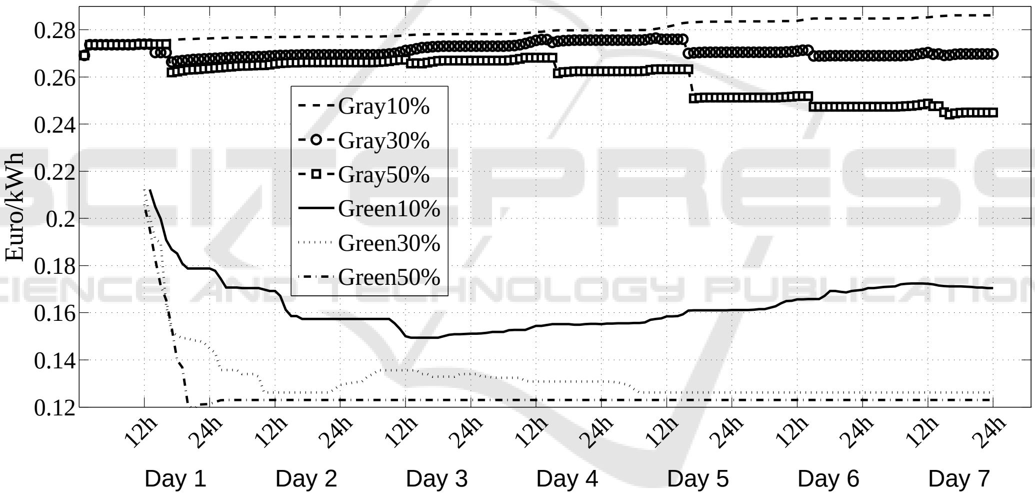

Figure 7: Gray and green energy prices during a whole week for different percentage of prosumers. Gray energy prices are mostly determined by the energy retailer but increase or decrease depending on green energy prices. Green energy prices are ruled by the market and influenced by availability or scarcity of green energy.

given energy market.

Figure 7 shows the behaviour of gray and green energy prices. Gray energy prices are negotiated between the substation and consumers/prosumers as explained in Section 3.1.2, whereas green energy prices come from a continuous double auction in which the only participants are prosumers and consumers (see Section 3.1.1).

On the one hand, the price for green energy shows a clear pattern, the more prosumers in a district, the cheaper the price. For instance, the price for green energy when the district contains 50% of prosumers is almost 0.12 Euro after the first day, whereas the price when the district has 10% prosumers is around 0.16 Euro. Moreover, regardless of the percentage of prosumers, green prices start relatively high and fall as green energy becomes abundant.

On the other hand, as an attempt to discourage the use of gray energy, the substation increases and decreases the price of gray energy based on whether green energy is abundant or not (see also Section 3.1.2). When abundant, the price for gray energy goes down. Otherwise, the price goes up. Consequently, as seen in Figure 7, the gray energy price follows the overall behaviour of green energy prices. It drops when green energy prices drop and increases

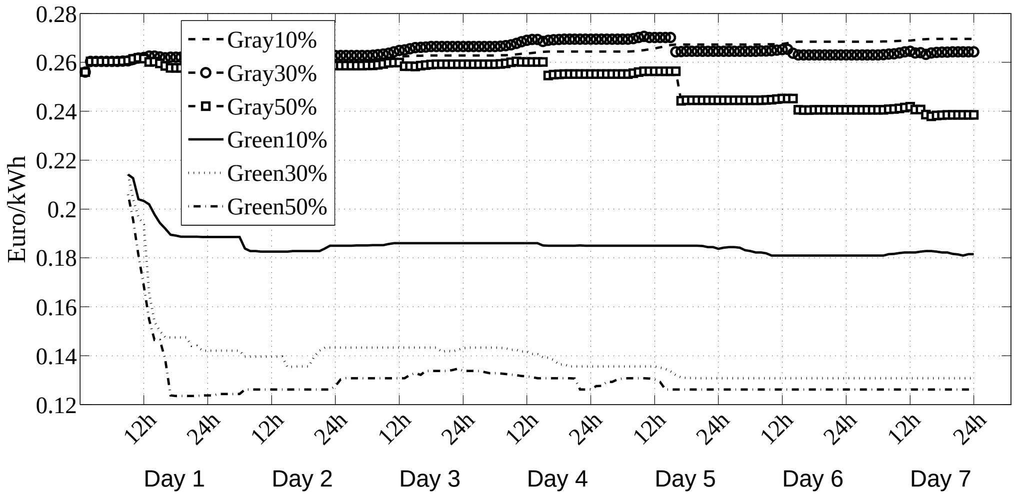

Figure 8: Gray and green energy prices during a whole week without storage facilities and for different percentage of prosumers. Prices for green energy are slightly higher than in Figure 7.

otherwise, which is the kind of behaviour we want to promote as consumers may be less willing to withdraw energy during those periods.

Finally, we have also tested the behaviour of green and gray energy prices when no storage capabilites are used. Figure 8 shows the behaviour of both prices. Although the overall behaviour is similar to the one in Figure 7, one thing is clear, the prices for green energy are slightly higher, which may suggest that storage helps to keep the price of green energy low. In our case, a possible explanation of the influence of storage in energy prices is that prosumers discharge their batteries when no green energy is generated, which may keep relatively constant the supply of green energy, i.e. green energy is less scarce and its price does not increase. Even though this aspect requires a more elaborated analysis, energy retailers as well as prosumers should acknowledge this when considering to invest in storage facilities since they could directly influence energy prices, which may potentially offer a good return on investment. In this way, retailers could try to keep profitable prices, whereas prosumers may try to ensure low prices when buying and high prices when selling energy. Moreover, the impact of storage in energy prices has been previously observed when energy retailers are equipped with storage (Prüggler et al., 2011).

5 CONCLUSIONS AND FUTURE WORK

We present the application of a multi-agent system to analyze the impact of load shifting and storage to reduce gray energy demand. In addition, we simulate energy markets in which green and gray (non-environmentally friendly) energy are locally traded. Green energy is traded using NRGcoins under the NRG-X-Change mechanism, whereas gray energy is traded in Euro via a bi-direcctional negotiation between an energy retailer and users of energy, i.e. consumers and prosumers.

To reduce energy demand, users apply load shifting and storage capabilities. Storage, however, is only available for prosumers as they can generate and store their own power.

Results show that reduction is possible mostly during night time hours, when no green energy is generated. Although, the highest reduction takes place when districts contain 50% of prosumers, (moderate) reductions are also observed for lower percentages, which encourages us to continue exploring more intelligent strategies to achieve higher reductions.

Moreover, as NRG-X-Change is a trading mechanism based on a double auction, i.e. several actors trying to buy and sell resources, other mechanisms applying a similar approach may take advantage of our results. For instance, in mechanisms such as PowerMatcher, energy aggregators can further exploit the use of storage to influence price curves by strategically charging and discharging batteries. Furthermore, regarding the integration of load shifting and storage, an analysis as the one presented here can be done for other innovative energy markets, i.e. using multi-agent systems and real data to explore future but still realistic scenarios.

In this vein, our future work will focus on applying other strategies to exploit storage and load shifting. For instance, cooperative and coordinated ways to charge and discharge batteries can be applied to not only cope with demand but also influence energy prices. Similarly, load shifting can also be coordinated among prosumers and consumers. On the one hand, we can make sure that they all do not delay or re-start loads at the same time. On the other hand, we can also maximize the amount of demand being curtailed and provide more flexibility to retailers.

Additionally, we would like to investigate optimal planning for storage location (e.g. retailers and normal consumers owning batteries) and capacity as it can bring economic and energy-related benefits. The former because storage owners can profit from trading energy. The latter because well-dimensioned capacity can provide better flexibility for load shifting.

Finally, regarding prices for gray energy, we want to explore different pricing schemes, e.g. time-of-use, critical-peak or real-time pricing. These schemes could potentially provide better responses from customers and improve energy balancing. Nonetheless, the final message is that to enhance the integration of renewables into the smart grid, combination of storage and DR programs is worth exploring for economic and environmental reasons (Niesten and Alkemade, 2016).

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REFERENCES

Aghaei, J. and Alizadeh, M.-I. (2013). Demand response in smart electricity grids equipped with renewable energy sources: A review. *Renewable and Sustainable Energy Reviews*, 18:64 – 72.

Bosch (2016). Bpt-s 5 hybrid solar power storage. http://bosch-power-tec.com/en/bpte/produkte/storage_solutions/bpt_s_5_hybrid/vs_5_hybrid. [Online; accessed 04-February-2016].

Bush, S. F. (2014). *Smart Grid: Communication-Enabled Intelligence for the Electric Power Grid*. IEEE Press.

Capodieci, N., Pagani, G. A., Cabri, G., and Aiello, M. (2011). Smart meter aware domestic energy trading agents. In *Proceedings of the IEEMC '11 Workshop on E-energy Market Challenge*, pages 1–10, New York, NY, USA. ACM.

Gottwalt, S., Ketter, W., Block, C., Collins, J., and Weinhardt, C. (2011). Demand side management—a simulation of household behavior under variable prices. *Energy Policy*, 39(12):8163 – 8174. Clean Cooking Fuels and Technologies in Developing Economies.

Grid4eu (2016). Nice grid demonstrator. http://www.nicegrid.fr/. Online; accessed 04-February-2016.

Ilic, D., Da Silva, P., Karnouskos, S., and Griesemer, M. (2012). An energy market for trading electricity in smart grid Neighbourhoods. In *6th IEEE International Conference on Digital Ecosystems Technologies (DEST)*, pages 1–6.

Kok, J. K., Warmer, C. J., and Kamphuis, I. G. (2005). Powermatcher: Multiagent control in the electricity infrastructure. In *Proceedings of the Fourth International Joint Conference on Autonomous Agents and Multiagent Systems*, AAMAS '05, pages 75–82, New York, NY, USA. ACM.

Ma, H. and Leung, H.-F. (2007). An adaptive attitude bidding strategy for agents in continuous double auctions. *Electronic Commerce Research and Applications*, 6(4):383 – 398.

Mert, W., Suschek-Berger, J., and Tritthart, W. (2008). Consumer acceptance of smart appliances. Technical report, EIE project Smart Domestic Appliances in Sustainable Energy Systems (Smart-A).

Mihaylov, M., Jurado, S., Avellana, N., Razo-Zapata, I., Van Moffaert, K., Arco, L., Bezunartea, M., Grau, I., Cañadas, A., and Nowé, A. (2015). Scanergy: a scalable and modular system for energy trading between prosumers. In *Proceedings of the International Conference on Autonomous Agents and Multiagent Systems*, AAMAS '15, pages 1917–1918.

Mihaylov, M., Jurado, S., Van Moffaert, K., Avellana, N., and Nowé, A. (2014). Nrg-x-change: : A novel mechanism for trading of renewable energy in smart grids. In *3rd International Conference on Smart Grids and Green IT Systems (SmartGreens)*.

Nakamoto, S. (2008). Bitcoin: A peer-to-peer electronic cash system.

Niesten, E. and Alkemade, F. (2016). How is value created and captured in smart grids? a review of the literature and an analysis of pilot projects. *Renewable and Sustainable Energy Reviews*, 53:629–638.

North, M. J., Collier, N. T., Ozik, J., Tatara, E. R., Macal, C. M., Bragen, M., and Sydelko, P. (2013). Complex adaptive systems modeling with repast simphony. *Complex adaptive systems modeling*, 1(1):1–26.

Paatero, J. V. and Lund, P. D. (2006). A model for generating household electricity load profiles. *International Journal of Energy Research*, 30(5):273–290.

Prüggler, N. (2013). Economic potential of demand response at household level—are central-european market conditions sufficient? *Energy Policy*, 60:487 – 498.

Prüggler, N., Prüggler, W., and Wirl, F. (2011). Storage and demand side management as power generator's strategic instruments to influence demand and prices. *Energy*, 36(11):6308 – 6317.

Ramchurn, S. D., Vytelingum, P., Rogers, A., and Jennings, N. R. (2012). Putting the 'smarts' into the smart grid: A grand challenge for artificial intelligence. *Commun. ACM*, 55(4):86–97.

Rickerson, W., Couture, T., Barbose, G. L., Jacobs, D., Parkinson, G., Chessin, E., Belden, A., Wilson, H., and Barrett, H. (2014). Residential prosumers: Drivers and policy options (re-prosumers). *Technical report, International Energy Agency (IEA)*.

Room, B. and Institute, W. R. (2010). Global ecolabel monitor 2010: Towards transparency. http://www.ecolabelindex.com/downloads/Global_Ecolabel_Monitor2010.pdf. [Online; accessed September,2015].

Schuler, R. (2010). The smart grid: a bridge between emerging technologies society and the environment. *The Bridge*, 40(1):42–49.

Shoham, Y. and Leyton-Brown, K. (2008). *Multiagent systems: Algorithmic, game-theoretic, and Logical Foundations*. Cambridge University Press.

Siano, P. (2014). Demand response and smart grids—a survey. *Renewable and Sustainable Energy Reviews*, 30:461–478.

Tesla (2016). Powerwall. http://www.teslamotors.com/powerwall. [Online; accessed February,2016].

van Werven, M. J. and Scheepers, M. J. (2005). The changing role of energy suppliers and distribution system operators in the deployment of distributed generation in liberalised electricity markets. Technical report, ECN-C–05-048, ECN.

VEA (2014). Vlaams energieagentschap - rapport 2013/2. http://www2.vlaanderen.be/economie/energiesparen/milieuvriendelijke/monitoring_evaluatie/2013/20130628Rapport2013_2-Deel2Actualisatie-OT_Bf.pdf. [Online; accessed 23-September-2015].

Vytelingum, P., Cliff, D., and Jennings, N. (2008). Strategic bidding in continuous double auctions. *Artificial Intelligence*, 172(14):1700 – 1729.

Wang, Z. and Wang, L. (2013). Adaptive negotiation agent for facilitating bi-directional energy trading between smart building and utility grid. *IEEE Transactions on Smart Grid*, 4(2):702–710.