Analysing the Impact of Storage and Load Shifting on Grey Energy Demand Reduction

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Abstract. We present an analysis on the application of load shifting and storage to enhance the use and penetration of green energy while decreasing grey (non-environmentally friendly) energy demand. We use multi-agent-based simulations that are fed with real data to analyse the impact of load shifting and storage on energy consumption as well as energy prices. We show results for scenarios in which storage is placed at different locations. In this way, results suggest that up to 15% reduction in grey energy consumption is feasible during peak times. Nonetheless, if the percentage of distributed renewable resources grows to 50%, higher reductions can be achieved, i.e. up to 50%. Finally, an important finding suggests that distributed storage helps to keep prices for green energy low.

Keywords: Smart grid · Multi-agent systems · Load shifting · Storage

1 Introduction

Engineering smart grids is a challenging task that must deal with new emerging actors, e.g. prosumers (energy consumers that can produce their own power), as well as with complex interactions between people, technology and natural systems [19,23]. Among those interactions, economic and power flows are of utmost importance [23,29]. Although novel mechanisms have been already proposed to not only optimise those flows but also improve the integration of renewable resources [4,7,8,12], they have not analysed the use of load shifting and storage to reduce grey energy demand and improve the integration of renewable sources.

As a way to analyse 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 to promote the trade and flow of locally produced green energy within dwellings [12]. 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 [13]. Unlike Bitcoins, NRGcoins are generated by injecting green energy into the grid rather than using computational power [12].

Although NRG-X-Change promotes the local trade and consumption of green energy between residential consumers and prosumers, it does not guarantee that

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green energy production fully matches consumption. In fact, when green energy is not enough to cover demand, consumers and prosumers will consume grey (non-environmentally friendly) energy to satisfy theirs needs and maintain a given level of comfort. To soften the dependency on grey energy, i.e. reducing its consumption, load shifting and storage capabilities can be integrated into NRG-X-Change. In this way, "original grey 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 [18], which may potentially inhibit trade and/or increase consumption.

This chapter extends previous work on the integration of load shifting and storage to reduce grey energy demand [20]. Compared to our previous work, the main contributions are the inclusion and analysis of scenarios in which storage is placed at different locations. In this vein, we perform numerical simulations using a multi-agent system that replicates the behaviour of main stakeholders, i.e. energy retailers, consumers and prosumers. Moreover, our simulations are fed with real energy consumption and production data provided by a Belgian distribution system operator (DSO).

The 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, 50% reduction can be achieved during peak hours if the number of prosumers reaches 50% and retailers as well as prosumers are equipped with storage, which is a plausible scenario for the coming years [21]. Furthermore, an important finding suggests that the use of storage influences energy prices.

The results of our research may help policy makers design appropriate incentives to boost energy storage and reduce consumption of grey energy. In addition, our results can help DSOs decide on the need for investment in storage. Likewise, they can also see the impact of load shifting in different scenarios and therefore allocate the necessary resources into the development of demand response programs.

The next sections are organised as follows. Section 2 presents related work covering aspects such as load shifting, demand response and negotiation strategies for energy markets. Later on, Sect. 3 describes the overall energy market as well as the physical setting. Finally, Sect. 4 shows results, whereas general conclusions and future work are presented in Sect. 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 [18]. 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 [1,5]. 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 [25].

Although several DR techniques and programs have been proposed in literature [1,25] and implemented in pilots [14] respectively, they all agree on an important issue: residential customers offer a lower potential for demand reduction compared to commercial and industrial consumers [1,5]. Likewise, in [5,17], 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 grey 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 [7] 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 [8] 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 [4], 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 [32]. The trade takes the form of a bi-directional process in which a seller, e.g. grid operator, continuously adapts (submits) prices for energy (asks), whereas 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 optimisation techniques (PSO-AABS).

Similar to Nobel and PowerMatcher, NRG-X-Change presents a market mechanism to locally trade energy between consumers and prosumers [12]. 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 [12]. To trade NRGcoins, consumers and prosumers participate in a continuous double auction (CDA) [24], 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 [9,11].

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 grey energy, however, we apply a negotiation approach based on AABS as this type of negotiation mimics retailer's control on grey 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 [29]. 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.

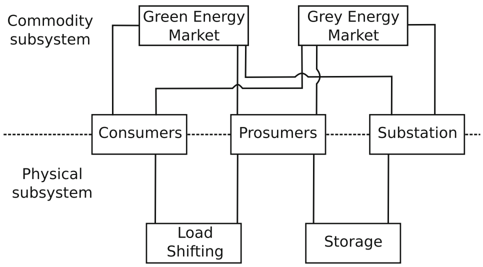


Fig. 1. High level description of our simulated electricity system (ES), elements and relationships are adapted from [29].

In our case, as seen in Fig. 1, we assume that the commodity subsystem is composed of green and grey 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. The next paragraphs elaborate on each subsystem.

3.1 Commodity Subsystem

Green Energy Market. We use the NRG-X-Change mechanism to allow the flow and trade of green (solar) energy between prosumers [12]. 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, she will earn NRGcoins accounting for that amount of energy, based on the local supply and demand measured by the substation [12]. 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 [12].

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 [31]. AAggressive is composed of four basic blocks: *equilibrium estimator*, *aggressiveness model*, *adaptive layer* and *bidding layer* [31]. 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 [31]. 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 and the maximum bid is 0.215 Euro, which is the estimated average price for residential customers in Belgium during 2014 [30]. On the other hand, limit prices for buyers and sellers were randomly defined in the range 0.01 and 0.215 Euro.

Grey Energy Market. In [12], the authors allow prosumers trading green and grey energy with NRGcoins. In this work, however, to trade grey 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 [22].

Since prosumers and consumers must consume grey energy whenever there is a lack of green energy, prosumers and consumers use the AABS strategy to negotiate prices for grey energy with the substation [32]. As described in Sect. 2.2, the AABS strategy relies on a bi-directional 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 grey energy goes down, otherwise it goes up. The idea is to discourage consumers and prosumers of using grey energy. This way, if grey 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 grey energy anyway.

To decrease or increase grey energy prices, the AABS' L_2 parameter [32], which is used to modify the substation's reservation price, is continuously adapted using Eq. 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 Sect. 3.1). 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 [32].

3.2 Physical Subsystem

Overall Architecture. In this work we use real-world data that has been provided by a Belgian DSO. 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 min, which are standard time slots in the electricity system [3].

Storage. In our setting we assume substation and prosumers are the only ones using batteries. The former can store the excess of green energy production in the grid, whereas the latter can generate their own energy and store their excess after satisfying own consumption.

Prosumers. 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 [28], whereas Bosch's offers storage of 4.4 and 13.2 kWh [2] 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 4 kWh capacity have been already installed in the French region of Carros [6]. 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 [2,28].

Substation. By the same token, although we are aware of commercial batteries offering different storage capacities [26,27], we define a lower boundary of 50 kWh for the substation's capacity. Tesla's Powerpack offers 100 kWh and Socomec's storage solutions (which were installed within the NiceGrid project [6]) offer capacities from 33 kWh to 100 kWh. Finally, we also assume an efficiency of 90%, for both charge and discharge [26,27].

Load Shifting. As previously reported in [10], loads associated to devices such as washing machines, dish washers, tumble dryers and air conditioners might be "easily" shifted since they not only account for 20% to 30% of the overall consumption [16] but also presented the highest willingness to postpone start according to residential customers [10]. 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 grey 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 h, i.e. 2 to 12 slots, as reported in [10].

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, she can only do it with a probability of 0.5. If probability is in her favour at that time slot, she can start shifting the load, otherwise she 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 [10].

4 Preliminary Results

4.1 Simulation Settings

To understand the impact of load shifting and storage for grey energy demand reduction and energy trade, we use a multi-agent system that is implemented in Repast simphony [15]. The multi-agent system is fed with real consumption and production data provided by a Belgian DSO. 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. First, regarding storage, we study three scenarios in which storage capabilities are located at different points.

Scenario 1: Includes storage for all prosumers only. The storage capacities are randomly assigned between 4 and 7 kWh.

Scenario 2: Includes storage being located only at the substation, i.e. prosumers cannot store their excess of energy. The power stored by the substation comes from prosumers' excess of energy, which can be used by both prosumers and consumers to match their energy demand. In other words, the substation battery is not charged with energy coming from outside the district, nor discharged to other districts. Moreover, as explained in Sect. 3.2, the capacity of the substation is set to 50 kWh.

Scenario 3: This scenario represents a combination of the former two scenarios as it includes storage for both substation and prosumers.

Second, regarding load shifting, for all the scenarios load shifting is always applied in both consumers and prosumers. Finally, due to the plausible increase of prosumers within the electricity system, and as an attempt to understand future conditions, we present results for settings containing higher percentage of prosumers for all scenarios [21].

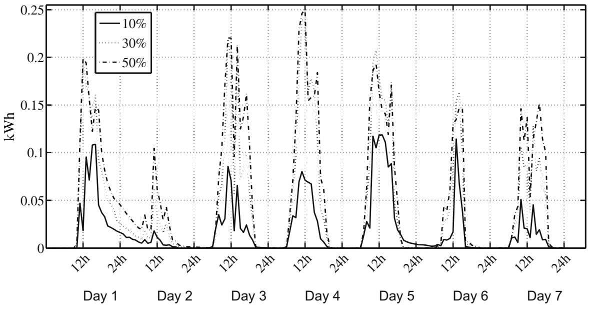
4.2 Energy Consumption

In this section we present plots of the average amount of grey and green energy being consumed by both prosumers and consumers. We show values for a typical

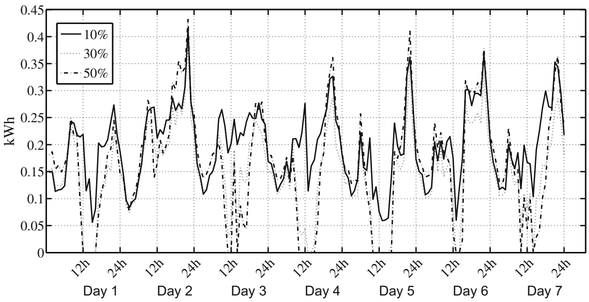
Belgian district, i.e. prosumers account for 10% of households, as well as for futuristic settings in which the percentage of prosumers are respectively 30% and 50%. To achieve these percentages, we fed real consumption and production data of 18 and 30 prosumers respectively in our simulations. These numbers represent the 30% and 50% of households in a typical Belgian district (usually composed of 60 households).

Figure 2(a) 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 Fig. 2(a), green energy consumption is observed during night hours between the first and second day.

In the same vein, Fig. 2(b) depicts the average consumption of grey energy, which shows that the more prosumers, the less grey energy is demanded during daytime hours. Unlike, green energy consumption, grey energy consumption



(a) Average consumption of green energy.



(b) Average consumption of grey energy.

Fig. 2. Average consumption of green and grey 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. Note that when the percentage of prosumers is above 30%, consumption of grey energy reduces considerably during daylight hours.

occurs mostly at late afternoon and early morning, when green energy is not generated. Consequently, it is important to reduce the energy consumption during those periods as prosumers and consumers will mostly use grey energy.

4.3 Consumption Reduction

In order to determine whether reduction in consumption can be achieved using load shifting and storage, we have analysed the overall consumption, i.e. green and grey 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 substation is expected to face. Moreover, it also shows the average reduction being achieved (dotted line).

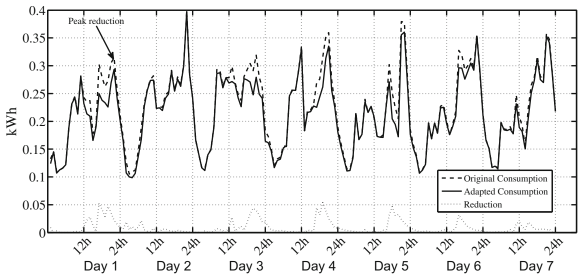
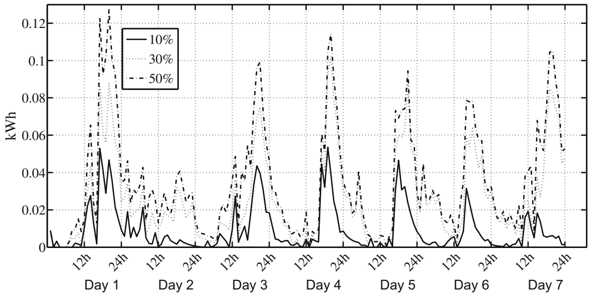


Fig. 3. Average values for original and adapted consumption (storage and load shifting capabilities) per household in a typical Belgian district with 10% prosumers. The dotted line represents the average reduction in consumption per household.

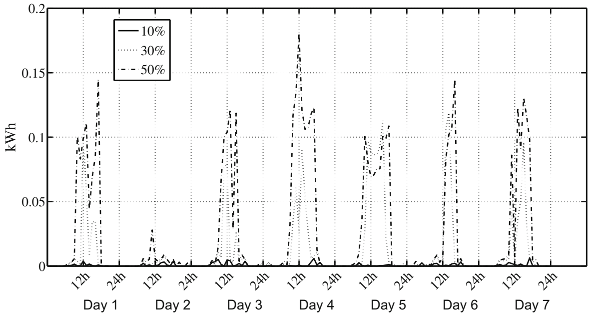
Although peak reduction can be achieved for some days, such reduction is moderate as the highest reduction is around 0.05 kWh, which is approximately a 15% reduction compared to the original consumption. Nonetheless, most of the peak reduction takes place at night time, when green energy is not generated,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

As explained in Sect. 4.1, we have also analysed three different scenarios to determine whether a higher reduction can be achieved in the near future. The results are presented in the following paragraphs.

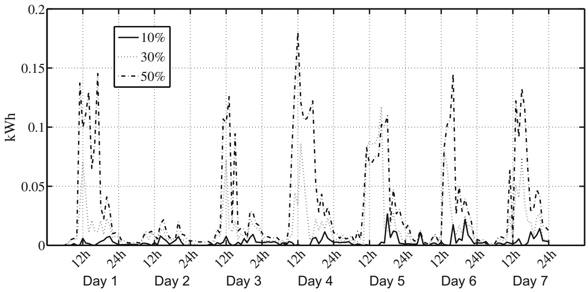
Scenario 1: Figure 4(a) shows the average reduction when storage is only available for prosumers and the districts contain 10%, 30% and 50% of prosumers. The highest peak reduction is achieved by the district with 50% prosumers and is above 0.12 kWh, which represents a reduction of at least 30% compared to the original consumption.



(a) Reduction when storage is only available for prosumers.



(b) Reduction when storage is only available for substation.



(c) Reduction when storage is available for both prosumers and substation.

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

Scenario 2: Figure 4(b) shows the average reduction when storage is only located at the substation. This time the highest peak reduction is around 0.17 kWh, which is about 50% of the original consumption. This reduction is achieved again in the district with the highest percentage of prosumers, i.e. 50% prosumers. Unlike the first scenario, however, the reduction achieved by the district with 10% prosumers is very low.

Scenario 3: Figure 4(c) shows the average reduction for the case in which both substation and prosumers are equipped with storage. Like in the previous two scenarios, the highest peak reduction is achieved by the district containing 50% prosumers. Such reduction is also around 0.17 kWh and is approximately equivalent to 50% of the original consumption. The reduction achieved by the district with 10% prosumers is again moderate compared to the first scenario but slightly higher than in the second scenario. This result may suggest that placing storage at both substation's and prosumers' facilities can lead to better reduction in grey energy consumption.

To achieve the reductions presented in the previous scenarios, nonetheless, one must be aware of not only using load shifting for consumers and prosumers but also providing storage capabilities to (either) substation and (or) prosumers. The performance of both load shifting and storage is presented in the following sections, i.e. Sects. 4.4 and 4.5 respectively.

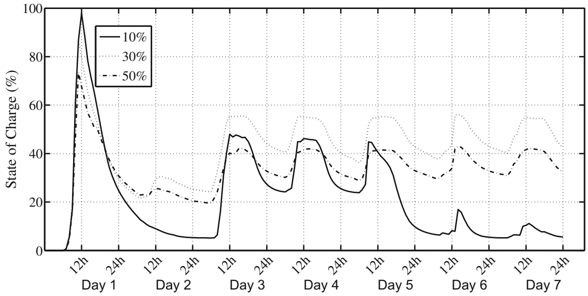
4.4 Storage

To determine how much green energy can be stored after prosumers cover their own needs, we measure the average state of charge (SOC) for both prosumers and substation. The SOC value indicates the percentage of charge of substation's and prosumers' batteries, i.e. how full batteries are, where 0% = empty and 100% = full. Similar to the previous section, we present results for the three described scenarios.

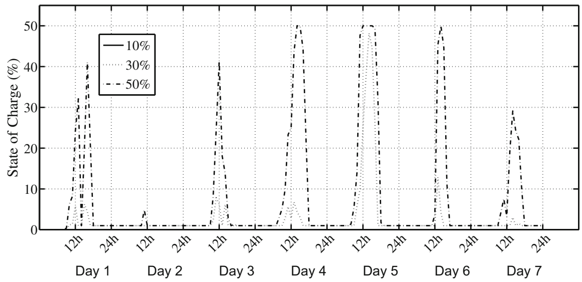
Scenario 1: Figure 5(a) shows the average SOC per prosumer when the substation is not equipped with storage, i.e. prosumers are the only ones capable of storing excess of energy. The figure depicts three lines, one per each setting, i.e. districts containing 10%, 30% and 50% of prosumers. As previously described, the capacity of the batteries can be from 4 kWh to 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 Fig. 2(a). Batteries, in this scenario, 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.

Scenario 2: Figure 5(b) shows the SOC of the battery located at the substation when prosumers are not equipped with storage. As can be seen, when the percentage of prosumers is 10% the battery cannot be charged as all the excess of energy is used by consumers and prosumers. Combined with the low reduction in consumption (see Fig. 4(b)), this may indicate that retailers should only consider adding storage to substations for districts with more than 10% prosumers. In this way, although moderate, the SOC increases as the percentage of prosumers



(a) Average SOC per prosumer when storage is only available for prosumers.



(b) Substation's SOC when storage is only available for substation.

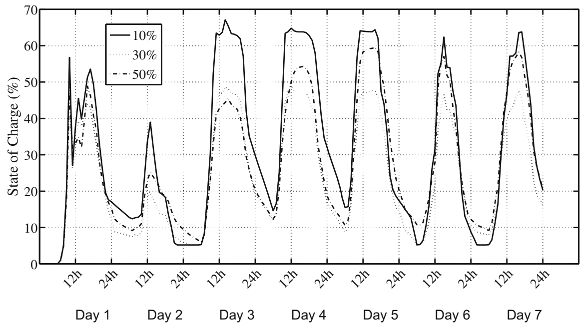
Fig. 5. Average state of charge (SOC) per prosumer for different percentage of prosumers. 0% = empty and 100% = full.

also increases since there is more excess of green energy during daytime hours, which helps to reduce energy consumption as seen in the previous section.

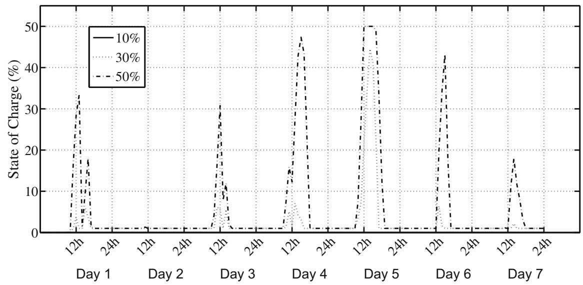
Scenario 3: Figure 6 shows the SOC for both prosumers' batteries as well as substation's battery. Figure 6(a) shows the average SOC per prosumer, which increases during daytime hours and decreases during the evening due to discharges to satisfy energy demand. Unlike in Fig. 5(a), batteries reach higher SOC as storage is also available at the substation. In this way, when green energy is not available, prosumers can withdraw energy from substation's storage without discharging their own batteries.

Figure 6(b) shows the substation's SOC, which is similar to Fig. 5(b) since the substation's battery can only be charge when the percentage of prosumers is above 10%. The overall SOC for the districts containing 30% and 50% prosumers, however, are slightly lower than in Fig. 5(b).

Based on these results, we can discuss two relevant findings. First of all, drops in production (as during the second day) will not allow batteries to be completely filled as they will have to provide green energy at night time. Moreover, since



(a) Average SOC per prosumer when storage is available for both prosumers and substation.



(b) Substation's SOC when storage is available for both prosumers and substation.

Fig. 6. Average state of charge (SOC) per prosumer for different percentage of prosumers. 0% = empty and 100% = full.

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.

Second, load shifting could help to fill batteries as initial consumption can be delayed, which may give time to store green energy. For instance, contrasting scenario 1 and scenario 3, the average SOC during the first day in Fig. 5(a) is higher than during the first day in Fig. 6(a) since there are loads being shifted in scenario 1 as seen in Fig. 7(a). Therefore, it is important to note that since 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 to curtail 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 [10]. 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). Moreover, 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). In this way, when the chunks of all consumers and prosumers are aggregated, they can provide a considerable amount of curtailment per slot as depicted in Fig. 7. The following paragraphs present and describe the results per each scenario.

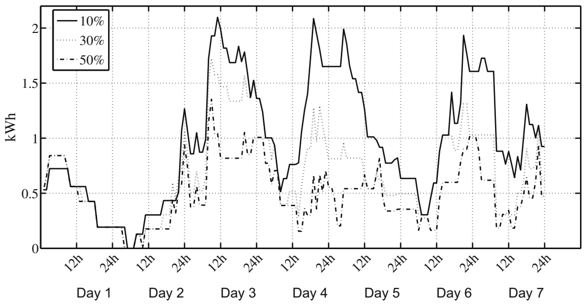
Scenario 1: Figure 7(a) shows the total demand being curtailed per time slot for three districts composed of 10%, 30% and 50% prosumers respectively. The highest amount of curtailment is observed in districts with low percentage of prosumers, i.e. 10% and 30%. The reason is that since green energy is scarce, i.e. prices for green energy go up (see also Sect. 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.

Scenario 2: Figure 7(b) shows the the total demand being curtailed when storage is located only at the substation. Unlike in the previous scenario, the highest amount of curtailment is lower than 2 kWh. Prosumers and consumers, as in the previous scenario, start delaying loads once the price for green energy also increases (e.g. see Fig. 8(b)).

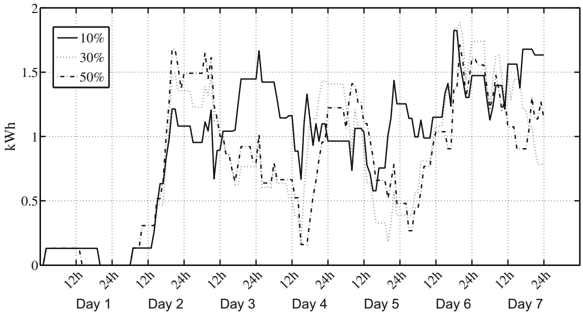
Scenario 3: Figure 7(c) shows the total demand being curtailed when both substation and prosumers have storage. Unlike the previous two scenarios, there are not loads being shifted during the first day since green energy can be obtained from either the prosumers's batteries or the substation's battery. Moreover, because of the same reason (storage available for prosumers and substation), the highest amount of curtailment is also lower than in the previous scenarios. Similar to the previous scenarios, however, the districts with lower percentage of prosumers tend to delay more loads as green energy is scarce.

4.6 Energy Prices

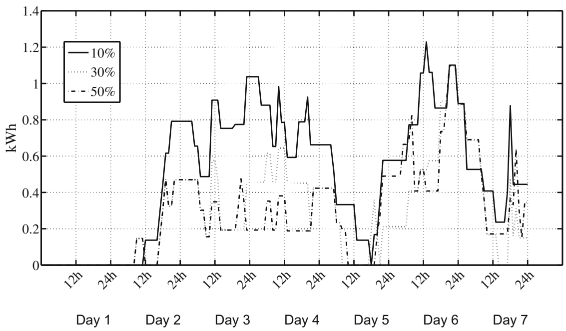
As not only energy-related measures are important to understand smart grids, but also economic aspects, we have also analysed the price behaviour of both green and grey energy. As explained in Sect. 3.1, grey energy prices are negotiated between the substation and both consumers and prosumers, whereas green



(a) Total demand being curtailed when storage is only available for prosumers.



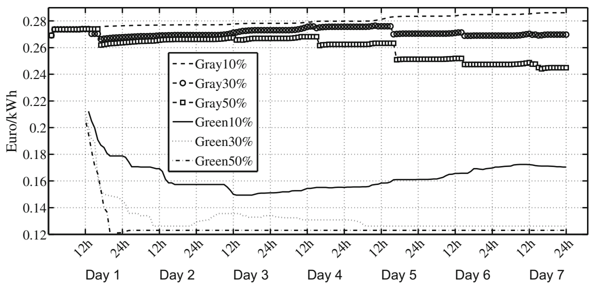
(b) Total demand being curtailed when storage is only available for substation.



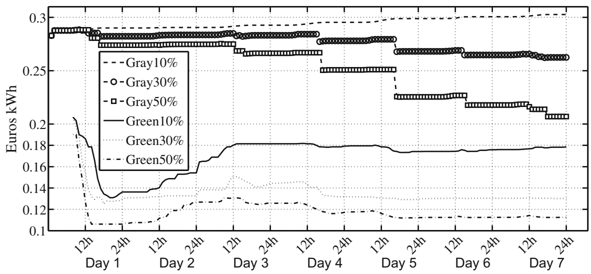
(c) Total demand being curtailed when storage is available for both prosumers and substation.

Fig. 7. Total demand being curtailed per slot over seven days.

energy prices come from a continuous double auction in which the participants are prosumers and consumers (see Sect. 3.1). The analysis of energy prices provides an idea about the expected profits or losses in a given energy market. Besides presenting results for the three described scenarios, we present results for an extra scenario in which storage is not available at all. The main motivation is to show the economic effect of adding storage capacity to the grid.



(a) Energy prices when storage is only available for prosumers.



(b) Energy prices when storage is only available for substation.

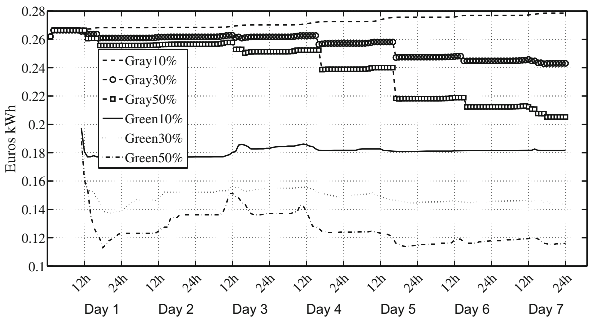
Fig. 8. Grey and green energy prices during a whole week for different percentage of prosumers.

Scenario 1: Figure 8(a) shows the behaviour of grey and green energy prices when prosumers are the only ones with storage capabilities. 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.

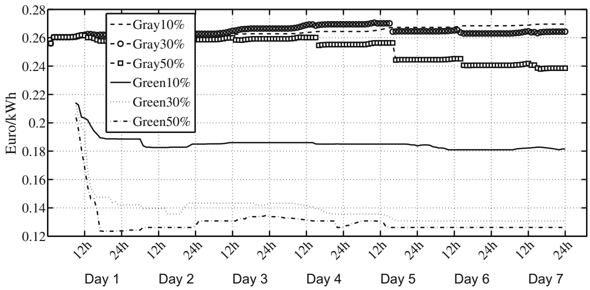
On the other hand, as an attempt to discourage the use of grey energy, the substation increases and decreases the price of grey energy based on whether green energy is abundant or not (see also Sect. 3.1). When abundant, the price for grey energy goes down. Otherwise, the price goes up. Consequently, as seen in Fig. 8(a), the grey energy price follows the overall behaviour of green energy prices. It drops when green energy prices drop and increases otherwise, which is the kind of behaviour we want to promote as consumers may be less willing to withdraw energy during those periods.

Scenario 2: Figure 8(b) shows the energy prices when only the substation is equipped with storage. Although the overall behaviour is similar to previous scenarios (the more prosumers, the lower the price for green energy), the price for green energy reaches its lowest point when the percentage of prosumers is 50%, i.e. the price for green energy after the fifth day is lower than 0.12 Euro. The overall prices when there are 10% prosumers are, however, slightly higher than in the previous scenario.

Scenario 3: Figure 9(a) shows the prices for energy when both prosumers and substation are equipped with storage. Like in the previous scenarios, the prices for green energy are lower in districts with higher percentages of prosumers. Moreover, once again, the price for green energy after the fifth day is lower than 0.12 Euro.



(a) Energy prices when storage is available for both prosumers and substation.



(b) Energy prices when storage is not available at all.

Fig. 9. Grey and green energy prices during a whole week for different percentage of prosumers.

Scenario 4: Finally, we have also analysed the behaviour of green and grey energy prices when no storage capabilities are used. Figure 9(b) shows the behaviour of both prices. Although the overall behaviour is similar to the previous scenarios, there is an interesting phenomenon since the prices for green energy are slightly higher, which may suggest that storage helps to keep the price of green energy low.

Even though this phenomenon requires a more elaborate analysis, retailers as well as prosumers should acknowledge this when investing in storage 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 on energy prices has been observed before [18].

5 Conclusions and Future Work

We use a multi-agent system to analyse the impact of load shifting and storage to reduce grey energy demand. Likewise, we describe an electricity system composed of a physical subsystem that provides the overall smart grid infrastructure (e.g. energy consumption and production, storage, and load shifting) and a commodity subsystem that support markets for green and grey energy. Green energy is traded using NRGcoins under the NRG-X-Change mechanism, whereas grey energy is traded in Euro via a bi-directional negotiation between an energy retailer and users of energy, i.e. consumers and prosumers.

We present results for three main scenarios in which there are different percentages of prosumers and storage is placed at different locations. Within the first two scenarios, storage is only available for either prosumers (scenario 1) or substation (scenario 2), whereas in the last scenario we allow storage to be allocated at both prosumers' and substation's facilities. The results show that reductions in grey energy consumption are possible not only for current renewables penetration rates (i.e. up to 15% reduction when prosumers are 10% in a district) but also for future scenarios in which the penetration of renewables will increase (i.e. up to 50% reduction when prosumers are 50% in a district). Furthermore, such reductions are mainly possible by combining load shifting an storage.

Regarding economic issues, prosumers, DSOs and retailers must be aware of the impact of storage and load shifting. DSOs and retailers must carefully consider investments in batteries at their facilities since when a considerable amount of prosumers is equipped with batteries, such investment may not be beneficial. In contrast, prosumers and consumers benefit from installing storage capacity as it will ultimately lower their electricity bill. Lastly, both DSOs and retailers should develop suitable demand response programs to incentivise load shifting, which may help them to better balance their customer portfolio and save in operational costs.

In this vein, our future work will focus on applying better strategies to optimise the use of load shifting and storage. We envision, for instance, the use of cooperative and coordinated ways to charge and discharge batteries, which can be applied to not only cope with demand but also influence energy prices. Likewise, load shifting can be coordinated among prosumers and consumers. In addition, we also want to improve the NRGcoin and NRG-X-Change concepts since they could potentially offer better economic incentives to stakeholders while promoting energy balancing within microgrids.

To conclude, our main message is that to reduce grey energy consumption while improving the integration of renewables, combination of storage and load shifting programs is worth exploring for economic and environmental reasons [14].

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