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Distributed Energy Storage Systems: Effects on Load Volatility

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43/2018 July

This project has received funding from the European Union Horizon 2020 Research and Innovation action under grant agreement No 649186

Distributed Energy Storage Systems: Effects on Load Volatility*

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August 11, 2018

Abstract

The diffusion of distributed energy producing systems relying on renewable sources poses a challenge to policy-makers, grid operators, and power generating companies in the electricity industry. One such case may be the diffusion of distributed storage systems integrated with photovoltaic units owned by households. On the one hand, they may act as a buffer and smooth the intra-daily variation in electricity flows through the network. On the other hand, they may increase volatility, if a large number of distributed generators simultaneously use the network once their batteries are fully discharged, by amplifying energy demand shocks. Under the latter hypothesis, the system costs would grow due to a need for larger back-up and transmission capacity, questioning the aggregate advantages of distributed storage systems. This work presents a stylised agent-based model to assess the likelihood of the two alternative effects of distributed storage systems of aggregate energy demand volatility, under different parametrisations of the power generation storage systems. The results suggest that distributed storage systems reduce fluctuations, and are thus beneficial at a systemic level, rejecting the volatility increase hypothesis. Further explorations through richer simulation models of the electricity system are welcome.

Keywords: Photovoltaic energy; energy storage; volatility.
JEL: Q4; Q42

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*The paper benefited from comments from participants at the SPRU50 conference. We acknowledge funding support from the European Union's Horizon 2020 research and innovation programme under grant agreement No. 649186 - Project ISIGrowth

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1 Introduction

Tesla's Powerwall has been hailed as a promising technological breakthrough in energy storage. By providing storage opportunities through a small-sized rechargeable lithium-ion battery that can be integrated with rooftop photovoltaic (PV) panels, the Powerwall meets the increasing willingness of consumers to save on the electricity bill and to set themselves free from the electricity grid, as highlighted by recent consumer surveys, e.g. in Galassi and Madlener (2016) or Agnew and Dargusch (2016).

One key motivation for energy storage lies in the quest for load stabilization (Fairley, 2015; Fumagalli, 2016). Power load is subject to wide changes during an average day, following the daily cycle in economic activities. The shortage of economically viable storage technologies has for long time prevented the achievement of a smooth profile in electricity network flows. The increasing penetration of renewable energy (RE) sources with supply varying according to weather conditions, has further complicated matters. Because of ramping costs and response time, most electricity generation technologies cannot promptly respond to the unpredictable variation in RE supply. The possibility of maintaining a reserve capacity may insure against surges of demand – which would disrupt the balance on the grid and cause blackouts – and, less predictable drop in RE supply. The stabilizing effect of storage is all the more needed in transmission grids that are frequently subject to congestion, which can be induced by RE as shown by Sapio (2015) and Ardian *et al.* (2015). Mitigating volatility would allow grid operators and utilities to delay the installation of extra generation and transmission capacity. Besides the sheer costs of a larger back-up capacity, volatile energy sources also reduce the utilization rate of conventional power plants, which therefore operate below their maximal efficiency and require more frequent maintenance. Energy-intensive manufacturing firms would also benefit from load-levelling and constant frequency in their power supplies (Whittingham, 2012).

While distributed storage systems (DSS), such as Tesla's Powerwall, may be appealing for households – once their installation costs and duration will improve (Johann and Madlener, 2014), their system-wide stabilising effects depend on the contemporaneous decisions of multiple interacting actors, and are therefore not easily predictable. The emergence of *prosumers*, enabled by distributed generation facilities, is seen as a destabilizing force for the incumbent technological paradigm (Sioshansi, 2014), which is based on centralised power generation, established in the early decades of the 20th century (Granovetter and McGuire, 1998).[1] Agnew and Dargusch (2015) illustrate some potentially disruptive effects of PV-integrated DSS on the overall performance of the energy system. Adding to these concerns, it is worth noting that because PV energy is not produced in off-peak hours, when electricity prices are low, storage integrated with PV does not provide access to the same arbitrage opportunities as storage technologies explicitly dedicated to smooth peak loads.

It is worth mentioning that even though in our paper we explicitly refer to PV production systems as the only RE source, we do so because our aim is to discuss a purely theoretical point and therefore adopt a simplified representation of an abstract energy distribution system. The same methodology could be expanded to consider also other forms of distributed and erratic energy sources, such as tidal energy or wind power, once a good approximation of the dynamics of these sources could be available.

The present paper contributes to this debate by comparing two possible effects on load volatility of an hypothetical large scale diffusion of distributed storage facilities integrated

[1] See Künneke (2008) for a comparison of the centralized and distributed generation paradigms from the perspective of evolutionary economics.

with renewable sources such as PV . First, in line with the existing literature on energy storage, distributed storage systems may *reduce* the volatility of electricity demand because batteries act as buffers. Supporting such expectation, DSSs decrease the users' necessity to access the network, whether on the supply or demand side. Thus, the aggregate intra-day load profile would be smoother if all users had access to energy storage.

Second, and opposite, DSSs may *increase* demand volatility by increasing the coordination of users. If the capacity of the storage systems is limited (comparable to the consumption level), and the production from RE in different sites is positively correlated, then a large number of distributed generators endowed with storage would simultaneously use the network, causing large jumps in the intra-day load profile. According to this hypothesis, we would observe that although small-scale volatility may be reduced by a large presence of DSS's, fewer but far larger un-balances would be faced by grid operators when a large share of producers suddenly flood the network with energy after having fully charged their batteries, or spike their energy request when all the stored energy is used up (at similar times in the day, by most consumers).

With a view to enhancing forecasts and improving the design of technical infrastructures and policy initiatives, it is crucial to understand which of the two effects is most likely to prevail (if any), and to assess the extent to which the likelihood of the two effects varies with respect to specific features of the system. If the second effect prevails – distributed storage facilities magnify volatility – then policy makers should carefully consider any policy intended to promote the diffusion of storage systems, for example subsidising the installation of PV and wind generators, ensuring priority dispatch to renewables in wholesale electricity markets, and fostering the adoption of distributed generation technologies (see e.g. the policies reviewed in Anaya and Pollitt (2015). The reason is that, in the second scenario the diffusion of storage systems integrated with PV would entail an increment of volatility and, consequently, the need to maintain a large amount of electricity production – possibly from polluting and costly power plants on the grid – to face volatile load peaks.

To investigate the effect of storage systems on volatility, in the presence of RE, we present an agent-based model featuring a large number of users equipped with electricity production systems from renewable sources, such as PV panels, installed in private homes. We assume that a share of the users have also a storage system coupled with their PV facilities. Under a number of reasonable assumptions concerning the mechanics of energy production and consumption, we analyse the effects of storage systems diffusion on the electricity system-wide volatility, the research question of this paper. We assess the size of the 'safety margin' for energy producers, that is, the share of electricity to be produced solely for the purpose of ensuring that a sudden load peak does not disrupt the demand-supply balance. The model provides a representation of a generic power grid comprising consumers, small-scale energy producers from renewable sources, and storage systems so as to assess the levels of volatility under a number of different scenarios.

The preliminary results suggest that the first effect dominates: as the adoption of batteries increase, the system fluctuations, measured as the sum of squares of one-minute variations in the network demand, reduces linearly. As the size of the batteries increases, the fluctuation reduce at an increasing rate, for all adoption rates. That is, storage system can contribute to reducing volatility of demand and, consequently, the size of the 'safety margin' that energy suppliers need to guarantee on top of current demand to ensure any short-term spike could be met without crashing the demand-supply balance. Reducing the safety margin have obvious positive consequences both in terms of saved fuel and lower pollution.

The paper is structured as follows. After reviewing the existing literature on the economics of energy storage in Section 2, Section 3 presents the agent-based model of the electricity system. The simulation results are described and discussed in Section 4 and Section 5 concludes.

2 Previous literature

Energy storage has long been felt as a needed technological innovation in the energy industry. Some of the main stylised facts about the liberalised electricity industry, such as volatility clustering and spikes, are seen as coming straight from the shortage of economically viable storage facilities (Graves *et al.*, 1999). While liberalisation has itself been a source of volatility in an industry previously organised as a regulated monopoly, further factors have contributed to spur volatility, such as tensions in fossil fuel producing countries (Sioshansi *et al.*, 2009). The literature has also highlighted the potential disruptions due to the increasing frequency and impact of climate change induced catastrophes, noting how the increasing penetration of RE sources (Beaudin *et al.*, 2010; Nyamdash and Denny, 2013) impact on the traditional management of electricity grid balance motivating research on the impact of energy storage technologies.

As observed in the introductory section, smoothing the short-term fluctuations of exchanged volumes in the electricity industry allows to save on costly reserve generation capacity, cycling-induced maintenance, network congestion, and network upgrades. Alongside such benefits, energy storage is seen as a powerful tool to facilitate the integration of RE technologies in the energy system, relieving issues that slow down their diffusion, such as high overhead costs, low predictability, or supply curtailments. Denholm and Margolis (2007) provided one of the earliest results showing that energy storage can enable the diffusion of solar power generation, followed by Sioshansi *et al.* (2009) on concentrating solar power. Sioshansi (2010) finds that storage enhances the value of wind power plants, using US data. Relatedly, Connolly *et al.* (2012) show that storage allows to improve the penetration of wind power in the electricity market, once investment costs are sufficiently reduced, using data on the Irish electricity system. Kaldellis and Kavadias (2009) underline the potential of energy storage for minimising the energy waste related to wind curtailments, occurring when the stability of the grid is threatened by excessive wind power production and grid operators force curtailments. Madlener and Latz (2013) explore the potential of compressed air storage integrated with wind turbines to balance the fluctuations of wind power production. Storage, moreover, can help improve the planning of new interconnections or substitute for them, whenever the correlations between load and the RE source is negative (Bell et al. 2015). This is particularly valuable as congestion sets is due to either load growth or to surges in RE supply. The strategic placement of energy storage systems may be more viable than the construction of new transmission and generation capacity.

The way storage technologies achieve a smoother intra-day load profile impinges upon arbitrage, induced by within-day electricity price excursions. Assuming price-taking behaviour and perfect foresight, Graves *et al.* (1999), Figueiredo *et al.* (2006) and Walawalkar *et al.* (2007), among others, have shown that the optimal arbitrage strategy by an agent, running an DSS integrated with a conventional power source, involves an all-or-nothing operation of the device. Specifically, according to the optimal strategy, the battery should charge until full capacity when market prices are low, typically in off-peak hours; should fully discharge at prices above the charge threshold, usually on-peak; and should remain idle at all other times. In other words, the deployment of storage should increase the generation of conventional power plants at night and decrease it during the day. According to the estimates reported in Bradbury *et al.* (2014), 4 hours of energy storage would be optimal for most storage technologies, given the round-trip efficiency parameters. Such an optimal size is anyway conditioned by the technology mix in the electricity market, by the growth in energy demand, and by congestion patterns, which affect the gap between on- and off-peak prices.

Along with smoother intra-day patterns in the use of the network, yielding less volatile wholesale electricity prices (shaving peaks and filling troughs), ESS can cause a redistribution of surplus from electricity producers not equipped with ESS to users who have installed a storage facility. As noted by Sioshansi *et al.* (2009), the lower energy demand off-peak implies that the decrease in consumer surplus from the higher price paid off-peak is more than offset by an increase in consumer surplus on-peak due to a drop in the on-peak price. Conversely for the generators who are not equipped with ESS. These welfare-enhancing effects depend on the governance structures linking storage operators, consumers, and power generators (Sioshansi, 2010), and have however been questioned by Hittinger (2017), noting that while the intra-day load profile flattens out, the overall level of energy consumption increases, possibly with growing climate-altering emissions.

Whether the above mentioned benefits materialise, and to what extent, depends on the specificities of the storage technology in use and the associated technical parameters. In a review of the literature, Beaudin *et al.* (2010) provided a thorough comparison of several energy storage technologies (pumped hydro, compressed air, batteries, superconducting magnetic, hydrogen, flywheels, capacitors and super-capacitors) in terms of their contribution to managing time variation in RE outputs (see Table 1 in their article). Batteries were found to be most suitable for maintaining power quality and grid stability, and to possess favourable properties, such as scalability, modularity, duration, and low maintenance costs.

The recently introduced Tesla storage device, a lithium-ion battery which exploits solar power, is expected to share the same advantages of other batteries and, what is more, is characterised by a longer duration than alternative batteries. Indeed, the life of e.g. lead-acid batteries is shorter than that of PV modules, which has been noted by Johann and Madlener (2014) as deteriorating the net present value of investments in storage and slowing down diffusion. The implicit tenet in the reviewed works on arbitrage, though, was that batteries could be charged by means of controllable energy sources, such as dispatchable power plants or pumped hydro (Nyamdash and Denny, 2013). This is not true with Tesla Powerwall, which can be charged only when the sunlight is available. The advantages of Tesla Powerwall in managing intermittent RE sources and mitigating volatility may not hold if the "optimal" arbitrage strategy cannot be implemented. The time pattern of battery charging and discharge, constrained by the availability of sunlight, is at the heart of our conjecture that DSS integrated with PV might make the network flows more volatile on an infra-day time scale.

From a methodological viewpoint, previous works assessing the value of energy storage have analyzed dynamic stochastic programming models, both for computing the optimal arbitrage profile from the perspective of an individual investor and in order to find the optimal dispatch in an electricity system. The only agent-based model on distributed PV that we are aware of has been published by Palmer *et al.* (2015), who have studied the diffusion of PV generation systems under different support schemes, through a simulation model calibrated on Italian data, but does not address the fluctuation properties.

3 The model

In order to test our hypotheses we need to evaluate the volatility of the load balance on different hypothetical electricity distribution grids with different shares of PV and local storage systems. For this goal we develop a simulation model replicating reliably the behaviour of the elements affecting the variables of interests.

The model makes a number of simplifying assumptions, focussing on a fairly detailed representation of the daily energy demand from each consumer, the amount of energy produced from PV systems and the collective impact of distributed storage systems. This model can be considered as a first block of a more complete model of the energy system that, once extended as, may be used as a policy tool to be deployed to examine additional research questions and, in particular, evaluate the effects of different policy measures.

In the simulation time scale, a time step represents a real-time minute. Agents consume energy according to a pattern partly common to all consumers (depending on the time of the day), partly idiosyncratic to each agent, including both systematic and random variations. Consumers equipped with a PV system generate electricity which is used primarily for own consumption. Non consumed PV energy is sold to the network, unless the consumer/producer owns a dedicated, not fully charged, battery. When production is not sufficient to fulfil energy consumption, consumers endowed with a local storage system drain energy from their batteries, if available, before accessing the grid.

3.1 Consumers

The proposed representation is meant to simulate observed consumption patterns. The model represents N of consumers, each following the same consumption pattern with idiosyncratic variations, randomly distributed, variations. The consumption pattern follows a cyclical (daily) pattern defined for each minute of a 24 hours (1440 minutes) day.

Each consumer start their consumption pattern between 6:00 AM and 7:00 AM, randomly distributed. Energy consumption for each consumer is also randomly distributed around and average value μ.

3.2 Producers

A share of consumers, randomly extracted from the population, is assumed to be endowed with PV systems. These agents have the same energy demand as consumers and, in addition, produce electricity that is primarily used to satisfy the user's demand. In cases in which the user produces more energy than requested by current demand, the excess energy is fed into the grid reducing the overall load.

Energy production is modelled following a simulated daily solar cycle. Each consumer receives the same amount of light, though each PV system has a different maximum production. The distribution of production capacity is determined randomly at the start of the simulation (following a rule initialised by the modeller). The sunlight available for solar energy production to all producers is also subject to random modifications simulating varying weather conditions.

3.3 Storage systems

A share of producers, randomly chosen, is assumed to also own a local storage system, whose size is assigned randomly at the start of the simulation run. These producers use the energy in excess of consumption to charge their batteries, releasing electricity to the grid only when the batteries are filled up. In case of insufficient production, consumption is primarily served by the energy in the storage system, resorting to the grid when the batteries are emptied.

3.4 Formal description

The energy consumption of user i, $C_{i,t}$, is determined as a variation from the previous minute energy consumption level approximating a new consumption level $C^T_{i,t}$:

$$C_{i,t} = \alpha C_{i,t-1} + C^T_{i,t} \tag{1}$$

where α is the measure of the inertia of consumption; and $C^T_{i,t}$ is a random value drawn from a normally distributed function centred on a cyclical variable:

$$C^T_{i,t} \sim norm(C^C_{i,t}, Var_C) \tag{2}$$

The cyclical variable is computed as:

$$C^C_{i,t} = C_{min} + \frac{(sin(\pi + 2\pi\frac{(t+s_i)}{1440}) + 1) \times (C_{max} - C_{min})}{2} \tag{3}$$

where π is trigonometric constant 3.1416; C_{min} is the minimum consumption level; C_{max} the maximum consumption level; s_i is the user specific time shift representing the individual consumer consumption habits, expressed as a temporal differences in starting a daily cycle. This value is defined at the start of a simulation run drawing a random value from a uniform distribution between s^{min} and s^{max}:

$$s_i \sim U(s^{min}, s^{max}) \tag{4}$$

Energy net demand from the grid of each user depends on the amount of energy produced, if any, and of the discharge/recharge of the battery, if available. Such demand is positive when production and the flow from the sun and from the battery is not sufficient meet consumption. While batteries are charging (meaning production matches and surpasses consumption, and batteries not yet fully charged) net demand is null. Finally, net demand is negative when the energy produced surpasses consumption and batteries are fully charged. In this latter case the user is selling energy to the grid, increasing global supply. Formally:

$$E_{i,t} = C_{i,t} - S_{i,t} + \Delta_{i,t} \tag{5}$$

where $S_{i,t}$ indicates production from the PV plants and $\Delta_{i,t}$ the flow of energy from the batteries ($\Delta_{i,t} < 0$) or to the batteries ($\Delta_{i,t} > 0$). In short, the net demand is positive when batteries and production are not sufficient to cover energy consumption, and negative when production exceeds consumption and battery charging.

Energy production is computed as the product of the plant capacity (PV_i) times available sunlight (L_t), equal for all users:

$$S_{i,t} = PV_i \times L_t \tag{6}$$

where production capacity is determined at the start of a simulation run with a random value drawn from a uniform distribution:

$$PV_i = PV^{max} \times U(PV^u, 1) \tag{7}$$

Sunlight is computed as a cyclical variable representing the time of the day measured in minutes (T_t, computed as the remainder of the ratio $\frac{t}{1440}$) times one minus the clouds intensity (Z_t). The sunlight is zero during night and follows the upper section of a sinus function during the day from 6:00AM to 18:00PM:

$$L_t = \begin{cases} sin\left(\frac{2\pi(T_t-360)}{1440}\right) \times (1 - Z_t), & \text{if } 360 < T_t < 1080 \\ 0, & \text{otherwise} \end{cases} \tag{8}$$

The clouds intensity is computed as an inertial random walk:

$$Z_t = \alpha_z Z_{t-1} + (1 - \alpha_z) \times U(0;1) \times Z_{max} \tag{9}$$

where $U(0;1)$ returns a uniformly distributed random value between 0 and 1; α_z is the inertia of weather conditions; and Z_{max} is the maximal reduction of sunlight. The variable is constrained to take only values in the range [0; Z_{max}].

The battery charge variation depends on: current energy consumption $C_{i,t}$, the current production from PV $S_{i,t}$, the past level of the battery charge $B_{i,t-1}$, and the maximum capacity of the battery, B_i^{max}.

$$\Delta_{i,t} = \begin{cases} 0 & \text{, if } B_i^{max} = 0 \\ min\,(S_{i,t} - C_{i,t}; B_i^{max} - B_{i,t-1}) & \text{, if } C_{i,t} < S_{i,t} \\ -min\,(B_{i,t-1}; C_{i,t} - S_{i,t}) & \text{, if } C_{i,t} > S_{i,t} \end{cases} \tag{10}$$

The level of the battery charge is computed as:

$$B_{i,t} = B_{i,t-1} + \Delta_{i,t} \tag{11}$$

The excess energy produced and not used for consumption nor to charge batteries, is fed into the grid, and computed as:

$$G_{i,t} = max(0; S_{i,t} - C_{i,t} - \Delta_{i,t}) \tag{12}$$

As results of the model, we collect all the values for every variable from individual users and the aggregate variables (computed as the sums over every user). Moreover, we compute an index of demand volatility as a 1-minute volatility of net load variation of energy from the grid:

$$V_t = (\sum_{i=1}^{N} E_{i,t} - \sum_{i}^{N} E_{i,t-1})^2 \tag{13}$$

3.5 Main parameters

The model is meant to simulate a complex electricity grid and compute the aggregate properties concerning the load pattern in relation to different assumptions on the number agents (share of producers and share of storage systems) and their characteristics (e.g. capacity of PV plants and size of storage systems). To simplify the implementation we control many of the properties of the simulated system by means of statistical distributions defined with few parameters. All the features of the model may, however, be easily calibrated using data from real-world systems, possibly modified to include the outcome of specific policies, for example in terms of share of observed consumers purchasing PV production systems.

Par.	Description	Value(s)
N	Total number of consumers	10,000
C_{min}	Minimum regular consumption	0.05 Kw
C_{max}	Maximum regular consumption	2 Kw
Var_c	Variance of individual random variation per minute	1 Kw
–	Share of users owning a PV energy production system	100%
PV^{max}	Maximum PV capacity (0 means user has no PV)	2 Kw
–	Share of producers owning a storage system*	10% - 90%
B^{max}	Maximum capacity storage systems (0 means user has no storage)*	30 - 90 Kw
s^{min}	Max. anticipation time shift	-120
s^{max}	Max postponement time shift	120
α	Autocorrelation random individual energy consumption	0.7
α_z	Autocorrelation random common weather	0.7
Z_{max}	Maximum PV production reduction due to weather	0.5
PV^u	Maximum rate of underutilization of the PV production	0.5

Table 1: Parameter values tested in the results. Parameters marked with * are explored with multiple values.

Table 1 reports the main parameters used in the simulation runs presented in the next section (4).

Notice that the configuration tested assumes a system where all consumers are also producers. This assumption is adopted to test the hypothesis under extreme conditions, since any configuration with a smaller percentage of producers will necessarily reduce the volatility, and hence the probability that local storage system increase the volatility of the system.

4 Results

To illustrate the model properties and main result we use an arbitrary setting made of plausible values for the parameters (Table 1). We begin with the presentation of results for individual members of a grid, consumers and producers, then we show the aggregate properties of the whole system and, finally, we assess the effects of storage systems on the load volatility.

4.1 Individual users

We start by showing the shape of the consumption pattern assumed for individual consumers. Figure 1 presents the energy consumption $C_{i,t}$ for two sample consumers over two days (2880 minutes), and the population average consumption (black line). Every consumer follows the same overall pattern, shifted by a random time gap, and is affected by random noise.[2]

Consumers are also producers, endowed with PV plants with heterogeneous productivity levels (in the current initialisation we assume that all consumers have a PV plant, to study a case of extremely high volatility). Productivity is also influenced by the weather

[2]The model may be extended to adapt the consumption pattern may to reflect different typologies of consumers.

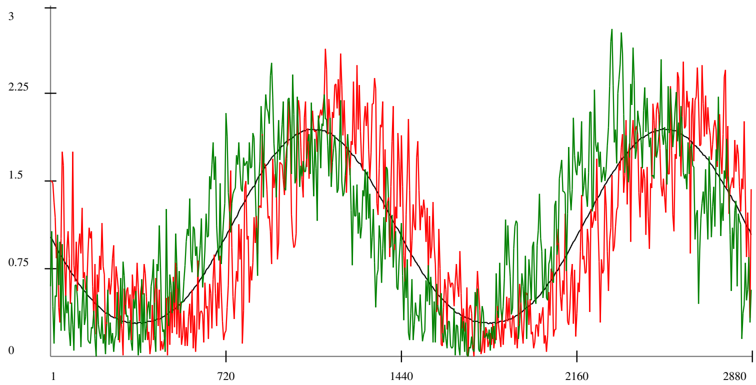

Figure 1: Energy consumption: population average and sample of two users.

conditions (common to all consumers), which also affects total production. Figure 2 reports the amount of energy produced by two sample producers $S_{i,t}$, in two days.

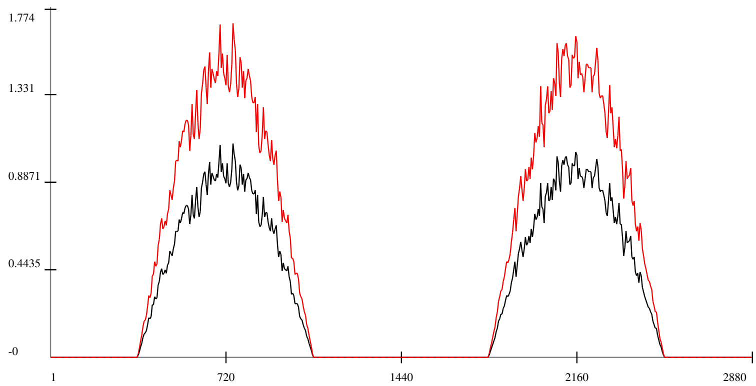

Figure 2: Energy produced by two sample producers.

A consumer owning a PV power plant may reduce the energy demand from the grid, and show a negative load when the production is higher than the consumption. Under those conditions some of the electricity produced by the consumers is returned to the grid. Figure 3 reports the series of energy consumption $C_{i,t}$ and the net demand from the grid for a consumer/producer $E_{i,t}$.

The horizontal line reports the null load. When the load touches this line the consumer neither draws energy from the grid nor feed in any electricity, that is the user has zero consumption or consumes exactly the same amount of electricity produced by the PV panels. When the load is above this level the consumer is using some energy from the grid, while when it is below the consumer is selling electricity back into the grid.

For those users endowed with a storage system, the energy produced but not used charges the batteries (if they are not fully charged). When, instead, the consumer demand is higher than supply, and they own a storage system, they use energy from the batteries. Figure 4 reports the charge level of the batteries $B_{i,t}$ for two sample producers endowed with a local storage system. Batteries are charged at a rate proportional to the efficiency of the PV system. When they reach the maximum level the excess energy is fed into the grid. When production terminates because of lack of sunlight the energy stored in the batteries is used and, finally, the user resorts to consume energy from the grid when the batteries are flat.

For producers owning a storage system the energy is not directly sold, but it is used,

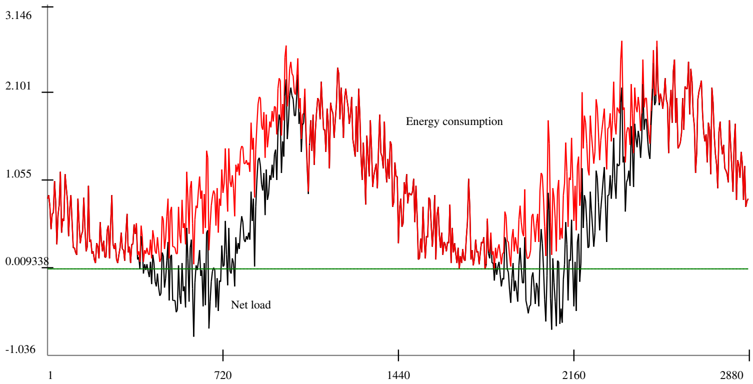

Figure 3: Consumer/producer. Energy consumption and net load on the grid.

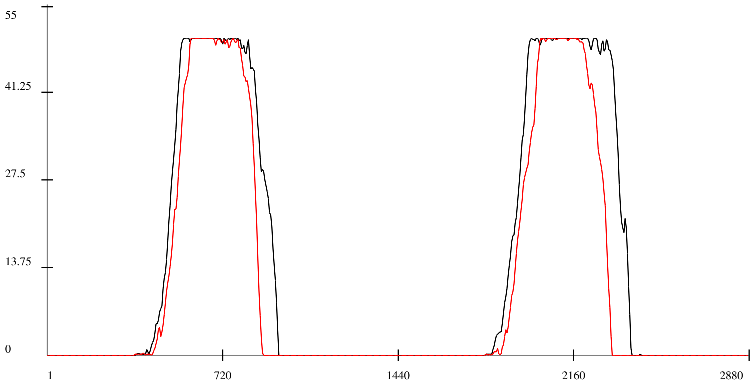

Figure 4: Battery level for two sample storage systems.

firstly, to fill up the battery. When the production falls below consumption needs, the energy is drawn from the batteries, and only when they are exhausted the consumer resort to the grid. Figure 5 reports the two series of consumption and net load for one user, as in the previous figure, together with charge level of the battery.

4.2 An empirical case study

The simulation results shown above, generated with arbitrary technical values, offer a qualitatively realistic representation of energy systems. Figure 6 reports, for comparison, the actual graph concerning the outcome of PV system coupled with a local storage[3].

The data are obtained for a system located in Rome during early April over two mostly sunny days. The production system has the maximum potential of 3 Kw/hour and the storage can contain up to 4 Kw. The data concern a two-day period beginning just before dawn with batteries completely flat. Consumption is initially relying on the grid but, at about 8:00 AM, the sun starts producing sufficient energy to meet consumption and charging the battery.

At about noon the batteries are filled up and the production begins to be sold to the grid. When the sun stops to power the PV panels the battery replace direct production. The high consumption level reduces rapidly the battery charge in early afternoon. During the night the low consumption is not sufficient to exhaust completely the stored energy.

[3]The figure reports the snapshot of the online control panel of a system by Sonnen, a German company providing storage systems integrated with PV plants.

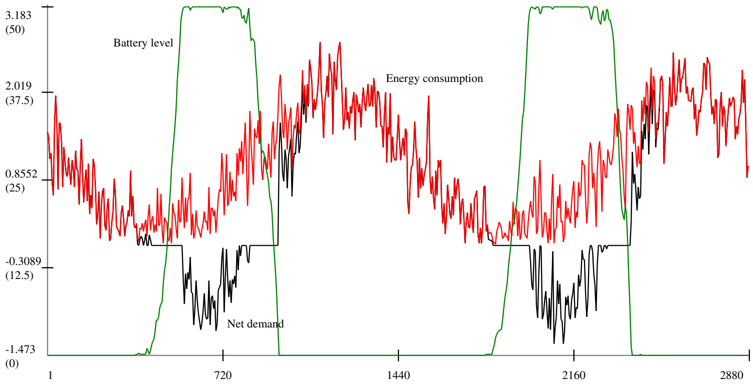

Figure 5: Consumer/producer. Energy consumption, net load on the grid and charge level of the batteries (last series measured on a different scale).

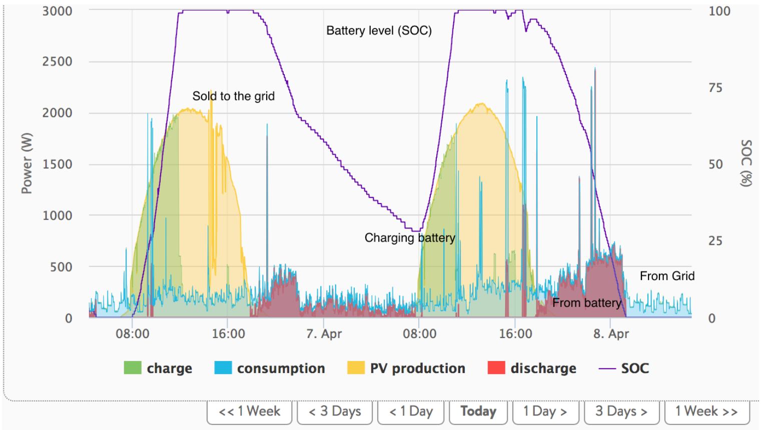

Figure 6: Real-world data for a two-day period of a 3Kw/hour PV system coupled with a 4 Kw storage. Snapshot of the online control panel by Sonnen.

The second day begins with some energy in the batteries, so that the sunny day manages to complete the recharge well before noon. However, higher energy consumption (around 4:00 PM and during the evening) depletes the battery just after midnight.

The qualitative comparison between the simulated data and the empirical case study suggests that our model replicates qualitatively the overall pattern of the energy consumption, PV production and effects of a storage system. While more precise data may be obtained, using them would require a far heavier computational effort to manage large datasets instead of simple functional representations as in the present version of the simulation model. For our purposes, assessing an overall property of the system, we consider the similarity between virtual and empirical data sufficient to consider the model a valid representation of real world systems.

4.3 Aggregate results: The impact of batteries on load volatility

Before testing the main hypotheses of our paper, we discuss the aggregate properties generated at system level by the interaction among the heterogeneous users in the model. Figure 7 reports all the relevant aggregate series for a single day, made of 1440 minutes.

The series labelled as *Tot. Consumption* indicates the total consumption by energy users ($\sum_i C_{i,t}$), represented conventionally according to a sinus dynamics, starting at

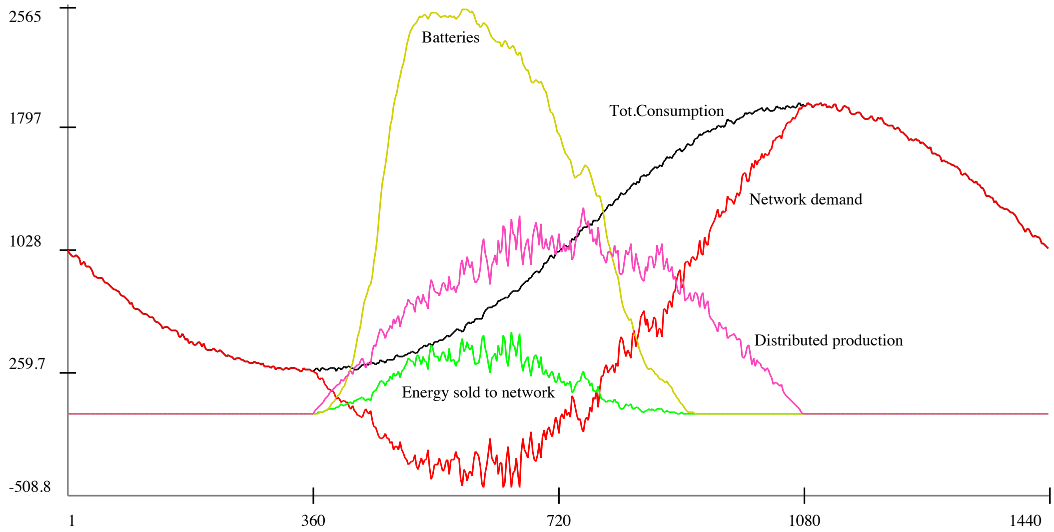

Figure 7: Time series for aggregate variables during a simulated day.

3:00am. The series *Network Demand* reports the electricity demanded from the network ($\sum_i E_{i,t}$), i.e. the net load. In the early hours of the simulations, during the night, there is no PV production, and thus all consumption must be satisfied by network electricity.

At 6:00am the simulated dawn allows for PV energy production to start (series *Distributed Production* ($\sum_i S_{i,t}$))), so that demand from the grid falls below total energy consumption. The PV production in excess of demand starts filling households' batteries, whose level begins to grow (series *Batteries* ($\sum_i B_{i,t}$)).

As more users fill up their batteries, the excess of energy is sold on the network (series *Energy sold* ($\sum_i G_{i,t}$)), generating consequently a negative network demand. As consumption grows, although sunlight peaks, PV energy production fails to meet demand, and the energy stored in batteries is used up, thereby decreasing their levels. Eventually, batteries are depleted, PV production falls, and network demand quickly catches up with total consumption.

The main goal of this preliminary simulation exercise consists in evaluating the impact of distributed storage systems on electricity demand volatility, to assess whether the diffusion of batteries would increase or decrease the size of the safety margin necessary for centralised producers to guarantee the overall network energy balance. For this purpose, we replicated the results varying the two parameters describing the extent of storage systems through their adoption and capacity: the share of consumers that own batteries, and the size of the average battery. With respect to the share of PV producers that also own batteries to store electricity we considered five values: from 10% to 90%, with intervals of 20%. With respect to battery capacity, we also considered 5 values: from 10KW to 90KW. Figure 8 reports on the vertical axis the level of volatility measured as the sums of squares of 1-minute variations in network demand cumulated over two full days.

On the horizontal axis the graph reports the size of the batteries, and the different

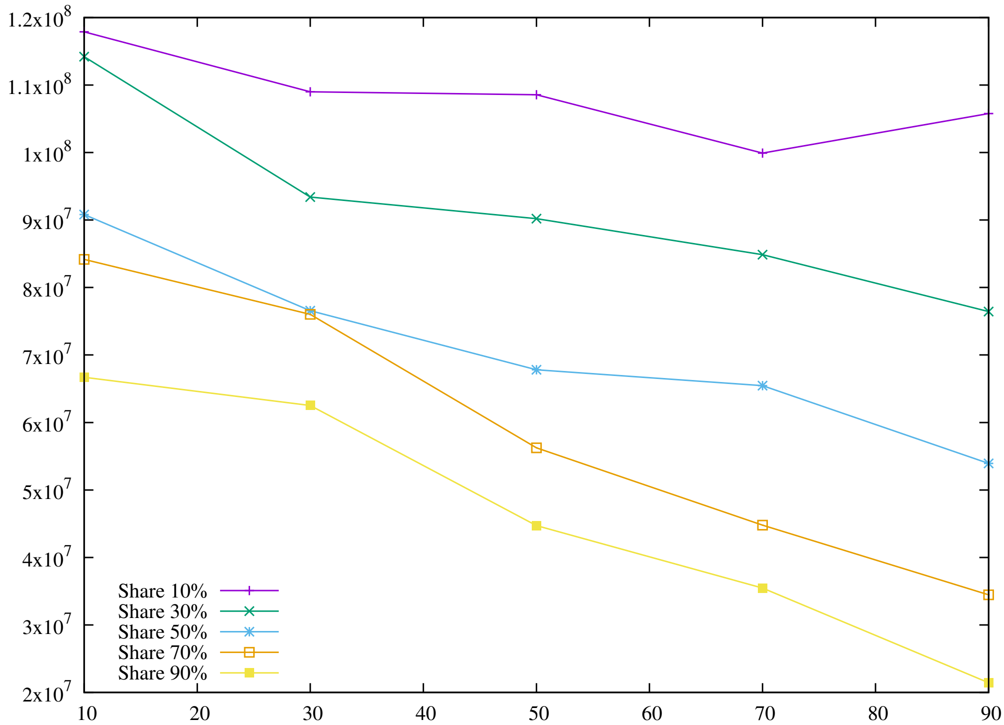

Figure 8: Total network energy demand variation over 1 minute, cumulated over all users and all time steps for a two-day simulation run.

lines connect the points referring to the same share of producers owning a storage system.

The results show that the volatility falls with increased diffusion levels of storage systems among PV energy producers and for increasing size of such storage systems. Thus, the model suggests that the volatility mitigation hypothesis is correct, rejecting the alternative hypothesis that storage systems may increase volatility in the presence of coordinated behaviour.

5 Discussion and conclusion

This work has presented preliminary results of an agent-based model developed to study the effects of energy storage systems integrated with distributed power generation. The results show that increasing the size of storage systems and their share in the population of energy users, reduces the aggregate electricity volatility of the network load, measured by the cumulated 1-minute variations in demand of energy from the grid.

Policy implications are therefore quite straightforward in this case, suggesting that there are only gains, at the systemic level, from improving battery technology, and promoting their diffusion among users.

The model presented in this paper is designed to be used for more ambitious goals and in a broader set of experiments. Concerning the issue of volatility of demand, it would be interesting to study specific forms of volatility of particular interest to default energy suppliers. For example, it may be possible that a low overall volatility may still include particular conditions with large jumps that may potentially concern central producers.

The model can be extended to include a more detailed representation of real-world energy systems. For example, the model may encompass heterogeneous producers, with differentiated costs and reaction times to changes in demand, in order to assess the best organisation of supply with respect to the rapidly changing needs of a demand sector in which the share of self-consumption is rapidly expanding. Moreover, the model may be extended to include *virtual* energy suppliers, who trade electricity obtained by coordinating actions of large consumers and fringe producers (reference). Within the shifting landscape of the markets for energy, constantly affected by technological innovations and policy initiatives aiming to mitigate the environmental impact of energy production, our model can be used as the foundation of a comprehensive tool assisting decision makers, such as policy-makers, regulatory authorities, network designers, and individual actors of the energy industry.

Besides the specific application discussed in this work, the model can also be calibrated with data from a specific system, and used to test alternative policy measures such as the effect of incentives, expected costs, load imbalances, and any other measure relevant to determine a regulatory framework able to best exploit the technological opportunities in the field of energy production and distribution.

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