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Value of energy storage aggregation to the electricity system

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ABSTRACT

Energy storage offers the flexibility needed to integrate renewable generation into electricity systems. One decentralized option is to install battery packs in homes and offices. Yet storage owners might operate their device autonomously to minimize their own electricity costs, but this could be inefficient from a wider electricity system perspective. Using a novel agent-based power system model, ESMA, we explore the economic trade-offs of aggregator-led (centralized) and consumer-led (decentralized) coordination in the UK over the period 2015–2040. We consider the deployment of storage in the domestic, commercial and industrial sectors.

Centralized scheduling leads to the lowest power system cost, reducing mean electricity prices by up to 7% relative to decentralized scheduling. This could avoid annual bill increases of up to 407 £m/year and could decrease electricity price volatility by up to 60%, depending on the installed storage capacity on the grid. We show that aggregators could reduce the disparity between private and system value by financially incentivizing consumers to give up control of their storage resource in order to use it more efficiently for the benefit of the wider electricity system.

1. Introduction

The proportion of electricity generated from uncontrollable renewables (wind and solar) and inflexible nuclear plants is rising rapidly in many countries. This increases the need for flexible technologies to ensure electricity security and affordability, and options include flexible generation, energy storage and demand-side response (shifting supply or demand in time), and reinforced networks and interconnections (shifting supply across space).

Energy storage can store excess renewable generation and provide electricity in periods of high demand. While some storage technologies have strong economies of scale (e.g. compressed air), battery electrochemical storage ranges from large grid-scale plants to small in-house battery packs. Control of energy storage could be centralized (scheduled by the System Operator) or decentralized (scheduled by the consumer for small, privately owned storage) (Rahbari-Asr et al., 2015). Centralized resources would likely compete in wholesale electricity markets via aggregators by offering balancing services to the electricity system. In contrast, decentralized resources would charge and discharge without consideration of the wider needs of the electricity system, and the system operator would see only a change in overall demand.

Small-scale electricity storage is typically paired with renewables (e.g. rooftop solar) to maximize self-consumption of variable renewable energy (Borenstein, 2017). Options include both dedicated in-house devices and vehicle-to-grid storage using the batteries of an electric vehicle (BEV) (Putrus et al., 2009). As the prices of solar PV and electric batteries fall, more consumers are expected to adopt these technologies (DECC, 2016b).

This paper investigates how centralized and decentralized coordination of consumers' generation and storage resources might affect electricity prices, in terms of both the average price and its volatility. We use these insights to propose a financial incentive that would encourage consumers to give control of their storage technology to aggregators, who could reduce power costs for the whole electricity system.

1.1. Consumer scheduling of electricity storage

Consumers are likely to choose to operate their energy storage device according to their objectives. Some contend that consumers would operate decentralized resources in a way that minimized their own bills (Borenstein, 2017; Hoppmann et al., 2014; Rodrigues et al., 2016). Yet retail electricity prices per kWh of supplied electricity are normally fixed, so the consumer cannot necessarily benefit from arbitrage in the same way as an aggregator.

For consumers with onsite generation (e.g. solar PV), the consumer could benefit from storage by minimizing overall electricity

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consumption from the grid, but only if the cost of importing electricity from the grid were higher than the income from exporting electricity to the grid during peak onsite generation. If most consumers were to generate at off-peak periods, when the wholesale price is low, then export prices would likely be lower. In the UK, solar PV generation occurs during daytime, while peak demand (and cost) is on an evening, and the current export price floor of ~£ 0.05/kWh is substantially lower than the retail price of ~£ 0.13/kWh. For this reason, here we assume that consumers would aim to minimize their electricity consumption for the grid, which would also minimize their total cost of electricity.

Another objective, for consumers seeking to maximize energy security, would be to keep the energy storage permanently charged in case of grid outages. This use of energy storage is not considered in this paper.

The deployment of generation and storage resources by consumers could influence the wholesale electricity market (Carbon Trust, 2016). A lack of coordination could lead to consumers charging instead of discharging their storage devices during high demand periods, causing higher electricity demand and price peaks. On the other hand, if consumer storage charging and discharging were strategically coordinated, it could substantially cut peak electricity demand and lower electricity prices (Acha et al., 2012).

1.2. Value to the electricity system of coordinating small-scale energy storage

The value of energy storage in balancing the electricity system depends on how it is operated to meet electricity demand. The roles and value of grid-scale energy storage to the energy system have been widely studied (Baker, 2008; Barbour et al., 2016; Denholm and Margolis, 2007; Denholm and Sioshansi, 2009; Greenblatt et al., 2007; Schmidt et al., 2017; Sioshansi et al., 2009; Staffell and Rustomji, 2016; Wade et al., 2010; Walawalkar et al., 2007). Centrally-controlled storage could generate large cost reductions in power systems with no flexible generation (Carbon Trust, 2012, 2016; Pudjianto et al., 2014).

Yet the value of aggregating small-scale storage compared to it being operated independently remains unclear. Aggregators can reduce transaction costs for small market agents due to their economies of scale in managing information and their marketplace centrality (Codognet, 2004). Aggregators offer value by making the system more flexible and enabling cost reductions when serving peak demand (Aghaei and Alizadeh, 2013; Basak et al., 2012; Basu et al., 2011; Marzband et al., 2013). By aggregating supplies (and demands), aggregators could provide a host of balancing and ancillary services, reviewed in Ofgem (2016). Aggregators could evolve into platforms through which even small agents provide and procure services such as operating reserves or voltage control (Burger et al., 2017).

A previous review of the literature and pilot projects by Niesten and Alkemade (2016) suggested that aggregation creates value only when performed at a large scale. In contrast, Calvillo et al. (2016) concluded that there is value in relatively small aggregations, with minor actions taken in response to aggregation signals by many distributed agents providing a substantial electricity system service. Studies of two US demand response companies indicate that aggregation could induce US $2–8/month in savings per customer, or a minimum saving from peak reduction of 4.5 GW (Burger et al., 2017; Opower, 2016). The value an aggregator may provide increases as more consumer resources are aggregated and may exhibit network effects (Katz and Shapiro, 1985). Centralized operation increases social welfare and lowers the cost of electricity, compared to decentralized operation (He et al., 2012; Jia and Tong, 2016).

1.3. Aims and structure of this paper

We have identified two gaps in the literature considering the impact of energy storage aggregation on the operational cost of electricity.

First, economic research does not account for potential future changes in electricity demands and supplies (He et al., 2012; Jia and Tong, 2016), which could greatly affect electricity prices.

Second, no previous study accounts for the load profiles of different types of electricity customers, nor uses these to define financial incentives that could induce a system-optimal use of consumers' storage and generation resources. Given the diverse load profiles of domestic, commercial and industrial electricity consumers, the value to each of privately operating storage is likely to vary.

Our work aims to address these gaps. Using a novel bottom-up power system management model we account for the behavior of domestic, commercial and industrial consumers, and consider different evolutions of the GB electricity system for the period 2015–2040. As market structures are key to this analysis, we also consider how retail price formation affects savings from consumer resources.

The remainder of this paper is structured as follows. Section 2 describes the methodology, focusing on the coordination of decentralized renewable and energy storage resources, and the design of a financial incentive to reward consumers for increasing system flexibility. Detailed information about the underlying methods are included in several appendices in the Supporting information. Section 3 reports our main results, which are discussed in Section 4. Concluding remarks are in Section 5.

2. Methods

We use a novel electricity system management model, ESMA ('Electricity System Management using an Agent-based approach'), to study the role of aggregators in coordinating consumer renewable and energy storage resources in Great Britain. We focus on the long-term evolution of the British electricity system in four scenarios that vary according to national economic prosperity and green ambition.

We specify the demand and supply sides in the wholesale electricity market, which the System Operator (SO) balances at each hour (see Appendix A). We consider flexible demand resources and renewable generation on the demand and supply sides, and account for three types of consumers: domestic, commercial, and industrial (see Section 2.1.4). The transport sector is included in the national scenarios since BEVs would increase system demand peaks if no control were used.

The model has an hourly temporal resolution and optimizes day-ahead scheduling of all resources. The indices t and d represent hour and day counters, where $t = 1, \ldots, T = 24$ and $d = 1, \ldots, D = 365$. Fig. 1 provides a simplified representation of the British electricity system. We model a set of consumer agents $A = \{a^1, a^2, a^3\}$ where each $a \in A$ represents a pool of consumers from each of the three sectors. Each consumer a has daily non-deferrable electricity and heat profiles, $l^a(t, d)$ and $q^a(t, d)$, representing activities which cannot be shifted in time, such as cooking. Consumers have access to flexible demand resources, including: electricity storage, heat pumps, and thermal energy storage (see Appendices B–E in the Supporting information), whilst a fraction of consumers generate PV electricity (Anon, 2016), storing any excess in an in-house battery modelled as Tesla's Powerwall1, due to its commercial availability (Tesla, 2017). The residual, or net, demand which consumers must purchase from the retail market is given by:

$$l^a_{net}(t, d) = l^a(t, d) - r^a(t, d) + l^{ch,a}(t, d) - l^{dc,a}(t, d) + l^a_{HP}(t, d), \quad \forall \quad t \in [1,T], \quad \forall \quad a \in A, \tag{1}$$

where $l^a(t, d)$is non-deferrable consumer demand; $l^{ch,a}(t, d)$, $l^{dc,a}(t, d)$ are consumer charge and discharge profiles (shown in Appendix G); $l^a_{HP}(t, d)$ is electricity demand from a heat pump and, $r^a(t, d)$ is electricity generation from a 4-kW solar PV polycrystalline system (DECC, 2013). Consumers are assumed to be able to sell any excess electricity generated through an aggregator in the market at the wholesale price. We do not model district heating, electricity trading, or ancillary

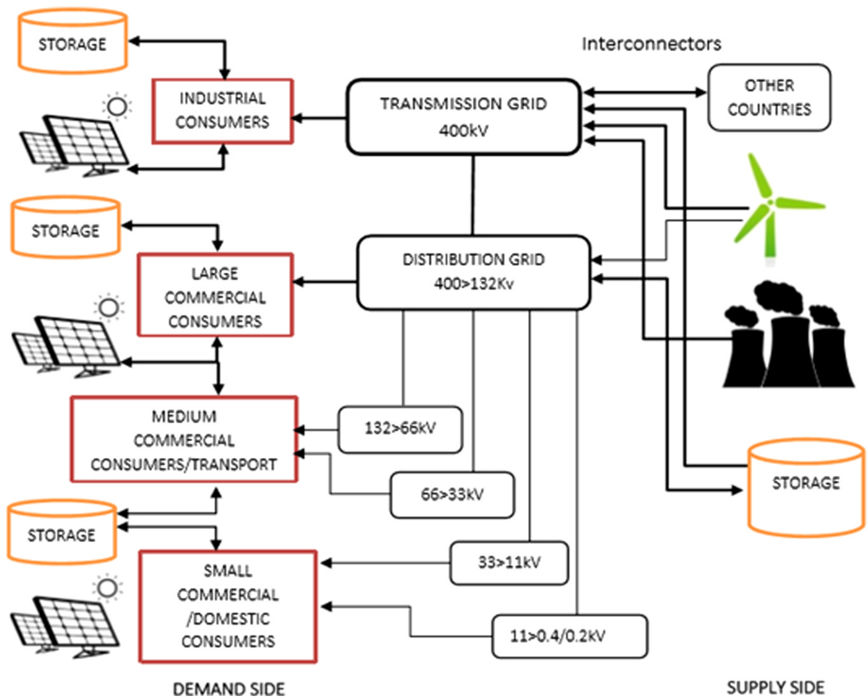

Fig. 1. ESMA's representation of the GB power system.

service markets, which could lead to us underestimating the *centralized* (but not decentralized) value of storage assets.

The market is modelled as a set of generators, $s = \{s^1,..,s^M\}$, where each $s \in S$ represents a group of electricity generation technologies of the same type. Generation from renewable resources $R(t, d)$ is modelled based on a historical generation profile from 2015, which is scaled in line with the installed capacity in the system. The SO stacks up available generator capacities, $K^S(t, d)$, offered at short-run marginal cost, $p^S_{SRMC}(t, d)$, and arranges them into a merit order. The electricity price $p(t, d)$ is determined as the demand-weighted price for a unit of electricity required to fulfil residual system demand (see Appendix F.1) including the operation of storage (Appendices A and E.3):

$$L_{net}(t, d) = L(t, d) - R(t, d). \tag{2}$$

As wholesale costs comprise $\sim 35\%$ of consumer bills (Ofgem, 2017), retail tariffs $\pi^a(t, d)$ are uplifted from $p(t, d)$ depending on the type of consumer a. Efficient pricing in a deregulated retail market generates prices that closely reflect the wholesale cost of electricity. Given the lack of information about the dependency of retail prices on wholesale market fundamentals, we consider three increasing degrees of co-variation between the retail uplift (mark-up) and wholesale demand and supply (see methods M1–M3 in Appendix F.2). M1 assumes a constant mark-up to wholesale prices per MWh; M2 assumes a mark-up that is dependent on demand and wholesale prices; whilst M3 assumes a mark-up that multiplies wholesale prices by a constant. M1 involves the lowest dependency on market fundamentals while M3 considers the largest degree of dependency, with M2 in-between. This methodology enables us to understand how retail price regulation can help realize the value of energy storage to the electricity system.

2.1. Demand-side resource coordination

Since electricity prices are set centrally, electricity cost-minimizing consumers would shift electricity demand to the same periods of low electricity prices, leading to 'consumer herding' and electricity price peaks. Previous scheduling algorithms (Gan et al., 2013; Ghasemi et al., 2016; Papadaskalopoulos and Strbac, 2016; Ramchurn et al., 2011) have been shown to overcome this problem by pooling consumers and allowing the aggregator to negotiate consumer demand curves by sending a signal. Yet effective implementation of aggregator-led scheduling requires participation from consumers and communication infrastructures that allow the aggregator to send that signal. An alternative approach to avoid herding is to allow the consumer to perform its own scheduling, but with the objective of smoothing demand rather than minimizing costs. This ensures that new demand peaks do not appear, whilst preserving full consumer autonomy. However, the net benefit of one approach over the other is uncertain.

2.1.1. Centralized coordination

In this paper, *centralized coordination* refers to the situation where consumer flexible resources are scheduled through an aggregator. We have identified three main approaches for performing this type of scheduling indirectly, or without an aggregator's control of consumer resources: *randomization*, *market-based control* and *iterative coordination* of consumer response.

Randomized control can be achieved in two ways: (i) consumers react differently to the same signal; or, (ii) react in the same way to different signals. For (i), stochastic load response can be deployed for the purposes of frequency control with a fleet of flexible resources such as electric vehicles (Ma et al., 2013; Meyn et al., 2015; Zhou and Cai, 2014) or thermostatically controlled loads (Hao et al., 2014; Tindemans et al., 2015). This approach is most appropriate for managing a fleet of similar flexible resources that can be stochastically switched on and off or react very quickly. It is not suitable for more complex demand scheduling. For (ii), the aggregator calculates different signals for each consumer, which allows its application to coordinating a pool of consumers (Boait et al., 2007; Mohsenian-Rad et al., 2010) or more generic flexible loads (Papadaskalopoulos and Strbac, 2016). However, the necessity of having a central entity that can calculate different signals introduces the issue of scalability as the number of consumers increases.

Market-based coordination allows consumption and generation agents to negotiate settlement through interactive bidding into the market, which is overseen by a third party (an auctioneer) which determines equilibrium prices and ensures network balance (Ghijsen and D'hulst, 2011; Kok et al., 2005).

Iterative coordination assumes an aggregator negotiating the demand profiles with a pool of consumers (or flexible demand units) over a number of iterations until the system converges. Convergence is achieved by either consumers or the aggregator adjusting (or learning) the strategy over the course of the negotiations. For example, in two studies (Voice et al., 2011; Vytelingum et al., 2010) the authors propose an algorithm in which consumers schedule demand based on the real time price in order to minimize costs. In order to avoid large swings in system demand, consumer response is suppressed through a damping term which penalizes them for shifting demand too much from the previous schedule. As a result of this algorithm, consumers slowly adapt to the market and reach a Nash equilibrium. Gan et al. (2013) applies iterative coordination for scheduling BEVs, but in contrast to another study (Ramchurn et al., 2011), where each iteration represents a day, all negotiations between BEVs and the aggregator take place during the day-ahead scheduling.

Whereas *randomization* and *market-based coordination* result in consumers reacting differently to the signal, *iterative scheduling* ensures the same ability for consumers to achieve cost reductions. Moreover, it represents a very flexible and adaptable approach which can easily be scaled and help integrate multiple flexible technologies. Hence, we chose the algorithm in Gan et al. (2013) for modelling centralized indirect coordination.

We assume that the aggregator negotiates consumer demand profiles over a number of iterations by sending them information about the average consumer load in a specific hour, which acts as a proxy for price. The algorithm works by suppressing consumer reaction to the projected wholesale prices of electricity and ensures convergence of the aggregate demand profile as shown on the left panel of Fig. 2. The resulting effect is smoothing consumer load rather than minimizing cost directly. For simplicity, we only consider one aggregator, so smoothing corresponds to the system residual load $L_{net}(t, d)$ calculated in Eq. (2). This also represents a case where the aggregator's interests are more closely aligned with the interests of the SO. An important consideration of the algorithm is that the aggregator does not need to know the resources to which consumers have access, preserving consumer privacy (see Algorithm 1, Appendix E.2, for details).

2.1.2. Decentralized coordination

Decentralized coordination mimics the behavior of consumers who individually schedule their flexible resources to reduce the cost of electricity (see Appendix E.1). The objective of the algorithm is to smooth demand rather than actively minimize cost, as this ensures that consumers do not herd towards the same periods of low electricity prices. Excluding wholesale prices from the scheduling methodology also means that consumers do not require a smart home metering device and communication with the aggregator. The objective function is calculated to minimize the variance of the consumer's residual demand calculated in Eq. (1):

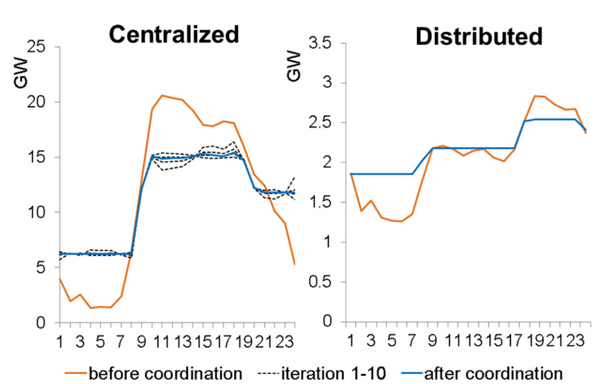

Fig. 2. Electricity demand under both coordination modes.

$$\min \frac{1}{T}\sum_{t=1}^{T}\left(l_{net}^{a}(t, d) - \frac{1}{T}\sum_{\tau=1}^{T} l_{net}^{a}(t, d)\right)^2 \tag{3}$$

Each consumer schedules its flexible resources to solve Eq. (3) subject to the technology constraints presented in Appendices B and C. Fig. 2 shows electricity system demand before and after centralized and decentralized coordination, highlighting the improved ability of the SO to minimize the system's total cost when it also coordinates consumer resources. Following consumer demand scheduling, the SO deploys pumped storage to smooth arising system demand peaks (see Appendix D).

2.2. Data and experimental scenarios

We consider four plausible evolutions of the UK electricity system based on National Grid's Future Energy Scenarios (FES) (National Grid, 2016). These scenarios represent the trade-off between future UK economic prosperity and green ambition and are: (i) No Progression; (ii) Slow Progression; (iii) Gone Green; and (iv) Consumer Power. Gone Green has the largest generation share from renewables and storage capacity, and the lowest fossil generation and carbon intensity. No Progression is most similar to the existing energy system, lying at the opposite end of the spectrum in all these areas. Gone Green meets demand by 2040 with a 34% renewable share due to the growth of wind, bioenergy and PV. The slower progress in the building and transport sectors means the scenarios reach the UK's overall target of 15% renewable energy later than the EU-agreed 2020 deadline, ranging between 2022 in Gone Green and 2029 in No Progression. The key statistics for each of these scenarios in 2030 are reported in Table 1. More detail on generation capacities and demand growth by scenario are in Appendix A.

We use electricity generation capacity by technology, electricity demand, fuel and carbon prices from National Grid (2016), and generation costs from the UK TIMES model (UKTM) (Daly et al., 2015; Fais et al., 2016), which is an energy system optimization model used by the UK Government (DECC, 2016a; HM Government, 2017).

To isolate the impact of storage, we decouple the national scenarios into system parameters and storage parameters. FES provides values for electricity and pumped storage technologies but not for thermal energy storage, which is set as described in Appendix I. Transport storage capacity is dependent on the expected growth of BEVs in the UK (National Grid, 2016). Table 1 reports the installed electric storage capacity for each of the four scenarios. The total number of consumers and their capacities are aligned with the UK's aggregate values for 2015 consumption (see Appendix G for data sources and related information). We considered 12 scenarios in total: 4 FES scenarios, each with 3 retail price specifications (M1–M3), which involve the 3 types of consumer cost optimizations (commercial, industrial, domestic).

2.3. Financial incentive to consumers for centralized coordination

If the System Operator could dispatch consumers' flexible resources to balance the system, it would be able to reduce electricity costs for all consumers in the system (Jia and Tong, 2016). Aggregators could profit from buying/selling electricity on wholesale markets to charge/discharge consumer storage (Rodrigues et al., 2016). Competitive aggregators would ideally share these profits with the consumers whose resources it aggregated for the benefit of the wider system. Aggregators should therefore be prepared to pay back each consumer for coordinating their flexible resources in light of the likely costs incurred by users by foregoing private cost optimization (Castagneto Gissey et al., 2017b). The maximum average amount that the aggregator should be willing to offer, ignoring capital, network, transaction and management costs, is equal to the excess operational system savings under centralized over decentralized coordination, at each hour, (i.e. the amount

Table 1
Key electricity statistics relative to each of the four FES scenarios in 2030 (National Grid, 2016).

	Gone green	Slow progression	No progression	Consumer power
Annual demand (TWh)	346	318	322	331
Peak demand (GW)	67	59	61	63
Total installed capacity (GW)	165	131	114	157
Low carbon capacity (GW)	103	78	53	87
Interconnector capacity (GW)	23	15	11	23
Electricity storage capacity (GW)	12	5	3	17
Fossil fuel capacity (GW)	20	31	47	33
Renewable energy (%)	31	27	21	23
Reduction in carbon emissions (%)	58	53	48	49

the system would save due to efficient coordination).

This incentive depends on the electricity system savings contributed by each consumer based on the different load profiles of domestic, commercial and industrial users, which imply diverse marginal contributions to system savings so are indicated as $i = 1, \ldots, 3$. The maximum payment which consumers could expect from the aggregator for coordinating their resources is the disparity between system and private benefits from resource balancing $\omega_t(i) = \lambda_t^c(i) - \lambda_t^d(i)$, where λ_t^d and λ_t^c are the total electricity system savings (see Appendix A, Eq. A6) in British pounds in the decentralized and centralized systems. The amount ω_t should ideally be redistributed to consumers based on their potential to improve system flexibility, which we define as the ability to store and release previously-generated electricity, S, a function of their load profile (see Appendix B). Then, $\Gamma_t(i) = \frac{\omega_t(i)}{S_t(i)}$ represents the aggregator's hourly compensation to consumer i for allowing use of their flexible resources to reduce system costs. Appendix J presents further information on this approach.

3. Results

We estimate the electricity system operational savings deriving from consumers' flexible resources and show how these are related to the electricity system-wide use of energy storage (Section 3.1). We then explore the impact of storage aggregation on wholesale electricity prices and their variability (Section 3.2). Section 3.3 reports the estimated aggregator's payments to coordinate consumers' resources when these are used to benefit the wider electricity system.

3.1. *Electricity affordability: consumer savings per unit of storage output*

Demand-side electricity generation and heat require storage to minimize consumer bills. Yet a suboptimal storage operation could unnecessarily increase system costs without contributing toward system savings from demand-side flexibility. Table 2 reports the estimated electricity system savings as a result of deploying demand-side flexibility, per unit of storage output (MWh_s) for each of the four national scenarios.

Table 2 implies that, when economic prosperity and green ambition are the largest (Gone Green), savings are on average 40 £m/MWh_s (per MWh storage output) under decentralized coordination, or 59% (24 £m/MWh_s) larger compared to centralized coordination. Gone Green is the only scenario where decentralized coordination yields greater savings per unit of storage relative to centralized coordination since it has the largest renewable capacity on both the demand and supply sides, leading to lower prices. The benefit from maximizing self-utilization of cheap power from renewables under decentralized coordination outweighs the savings obtained from peak shaving under centralized coordination across retail prices M1–M3, explaining the greater savings.

Centralized control generally enables greater system-wide savings from storage. In the Slow Progression scenario, savings from flexible resources are only 1.6 £m/MWh_s larger in the centralized case relative to those under decentralized coordination because the level of system flexibility is low due to low prosperity against the backdrop of low electricity prices, in turn due to high installed renewable capacity. In contrast, Consumer Power is associated with substantial storage capacity which generates large savings when it is aggregated.

Centralized coordination enables lower integration of storage resources than decentralized coordination when there is a lot of dispatchable capacity (e.g. gas) available relative to storage. In all other situations, it implies greater savings than decentralized coordination as more storage per unit of gas means greater savings per storage output. Under centralized coordination, domestic users contribute the largest savings (11 £m/MWh_s) relative to other users, but only if the retail price mark-up is constant. As the mark-up becomes more sensitive to demand, commercial users display the greatest savings. Domestic users achieve the largest savings when supported by decentralized coordination and highly variable mark-ups (95 £m/MWh_s), but these fall to zero under a constant mark-up. Autonomous behavior induces herding, so greater price peaks, and a mark-up that is sensitive to market fundamentals leads to more price volatility, increasing the utility of storage.

As the mark-up becomes more responsive to electricity demand, consumer savings from flexible resources generally increase, under both coordination modes. If the mark-up is constant, consumers display the lowest savings per unit of storage (0.6–33.9 £m/MWh_s). As the mark-up becomes more sensitive to market fundamentals, savings notably increase. With a mark-up only dependent on system demand, savings rise to 2.9–38.3 £m/MWh_s, and to 0.7–70.9 £m/MWh_s if it also depends on system supply. This suggests the disparity between system and private value is likely to become more pronounced as retail prices more closely follow wholesale fundamentals. Mark-ups less responsive to demand

Table 2
Operational savings per unit of electricity storage output (£/MWh_s) by type of coordination. Total installed electricity storage capacity is reported in Table 1. Average value for the period 2015–2040 are reported.

Retail price mark-up sensitivity to wholesale market fundamentals	Balancing coordination	Commercial			Industrial			Domestic		
		Gone Green	Slow Progression	Consumer Power	Gone Green	Slow Progression	Consumer Power	Gone Green	Slow Progression	Consumer Power
Low (M1)	Centralized	4.9	0.7	9	4.1	0.6	7.5	5.9	0.8	11.0
	Decentralized	18.4	0.1	1.1	5.3	0.1	1.2	33.9	0.0	0.0
Medium (M2)	Centralized	12.6	2.9	21.5	9.7	2.2	16.6	12.1	3.3	20.1
	Decentralized	38.3	0.8	7.2	22.4	0.9	5.9	61.7	0.5	0.7
High (M3)	Centralized	39.7	6.6	70.9	30.5	4.7	54.8	28.6	6.7	49.1
	Decentralized	49.0	4.4	52.1	39.8	3.3	39.3	94.9	4.0	35.3

Table 3
Mean wholesale electricity price by scheduling coordination of demand-side resources between 2015 and 2040.

Balancing coordination	Mean electricity price (£/MWh)			
	No progression	Gone green	Slow progression	Consumer power
Centralized	34	24.7	34.2	22.7
Decentralized		26.4	35.5	23.9

likely decrease the gap between system and private benefits from consumer resources. Unless the retail price mark-up is highly dependent on wholesale prices, centralized scheduling always favors storage-led savings more than decentralized scheduling. Further, a balanced ratio between renewables and aggregated storage capacity implies greater savings from volatile prices, as storage gains system utility.

3.2. Wholesale electricity prices by coordination regime

Table 3 reports the estimated electricity prices prevailing under centralized and decentralized coordination of demand-side storage resources. Decentralized coordination always leads to greater mean prices compared to centralized coordination, ranging between 25 and 34 £/MWh. Centralized coordination benefits from more resources devolved to smoothing system demand and may lower electricity prices by 4–7%, subject to total storage capacity.

As shown in Table 3, the lowest electricity prices occur under Consumer Power as the system displays the largest storage capacity and a substantial renewable capacity, especially under centralized coordination (22.7 £/MWh). On the other hand, the highest electricity prices occur under Slow Progression, which has high renewables but low storage capacity, implying greater pressure on prices, particularly under decentralized coordination (36 £/MWh). Prices drop substantially relative to the No Progression scenario, mainly when there is substantial renewable capacity (22–27%, Gone Green; 33–42%, Consumer Power), depending on the coordination modality. Even with little storage capacity, prices fall substantially due to aggregation.

3.3. Security: electricity price variability

Centralized coordination not only leads to lower prices but also to lower price volatility than decentralized coordination. This occurs because more storage enters the electricity supply after aggregation, reducing both the system's renewables to storage capacity ratio and renewable supply variability. Volatility under decentralized coordination is larger by at least 2–3% under decentralized relative to centralized coordination, as the SO is unable to maximize the integration of consumer storage. Fig. 3 illustrates the standard deviation of wholesale prices during 2015–2050 to assess volatility using an interpretable measurement unit (£/MWh). Consumer Power scenarios have the greatest storage capacity, so price volatility is larger in the decentralized case by a substantial 63%. Over the entire 35-year period, the average difference in standard deviation between the two coordination scenarios is 6 £/MWh.

3.4. Aggregator's willingness to pay to coordinate consumers' flexibility

Table 4 shows the aggregator's maximum willingness to pay to coordinate consumers' flexible resource capacity. Excess savings in the decentralized over the centralized coordination regime are the largest for domestic users, explaining the greater payment relative to other user types. This results from domestic users' spiky load, particularly at times of peak demand, which favors savings from storage. Industrial users, whose demand is relatively flat, are unable to substantially contribute toward system-level savings on the margin, whilst commercial users lie in between. Excess savings are the largest under Gone Green due to a large renewables-to-storage capacity ratio, which widens the gap between system and private benefits from energy storage.

Table 4 shows that mean hourly excess savings from centralized over decentralized coordination are on average £127k, £218k, and £181k, for domestic, commercial, and industrial users, respectively, across the national scenarios. Yet the system value of each unit of storage implies maximum payments by the aggregator of 121 £/MWh_s, 13 £/MWh_s, and 7 £/MWh_s, respectively. Domestic users require larger payments to be nudged into providing system benefits through aggregation, as their load profile is better suited to contribute toward electricity balancing at times of system stress. The greater spikiness of domestic loads induces greater private savings per unit of storage via individual operation relative to other users, explaining their larger reservation price.

4. Discussion

Our results suggest that centralized coordination of small-scale storage through aggregators could reduce wholesale electricity prices, and their volatility, compared to decentralized coordination. Yet

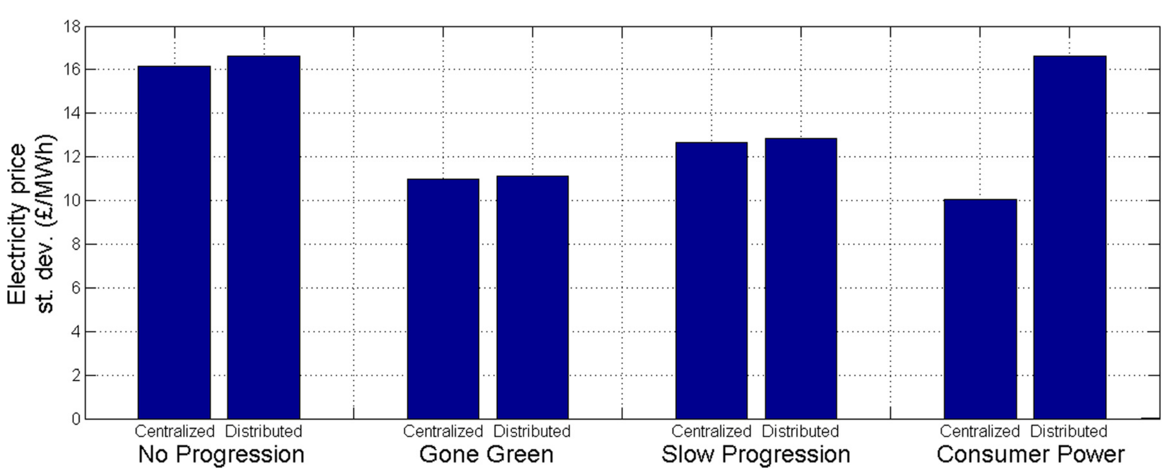

Fig. 3. Electricity price standard deviation by coordination and National Grid FES scenario, with a 40% renewable share.

Table 4
Mean nominal excess savings per hour (£/h) and aggregator's maximum average willingness to pay per MWh of storage output (£/MWh_s) to coordinate consumers' energy storage devices, by consumer and scenario.

	Consumer type	Gone Green	Slow Progression	Consumer Power	Mean
Nominal excess savings	**Domestic**	23,984	172,869	183,785	126,879
Aggregator max. payment		20	311	31	121
Nominal excess savings	**Commercial**	393,834	167,894	91,901	217,876
Aggregator max. payment		14	16	11	13
Nominal excess savings	**Industrial**	310,970	122,828	109,679	181,159
Aggregator max. payment		8	6	7	7

consumers would likely prefer operating storage autonomously in order to reduce their own bills. Because storage has a high capital cost, it is unlikely for consumers to use their devices to benefit the system. We therefore propose a financial incentive that an aggregator could offer to consumers to reflect the potential value of their storage devices to the electricity system.

4.1. Aggregator's flexibility payments reduce prices and improve security

Switching from private decentralized coordination of consumer storage to centralized coordination could decrease mean wholesale electricity prices in the UK, by up to 7%, or 1 £ /MWh. Under centralized coordination, the system minimizes costs more efficiently than the combination of many individual consumers who schedule their resources for their own benefit. The latter also causes simultaneous charging during peak demand periods, which inflates prices, whereas a centralized approach provides lower electricity prices under all examined evolutions of the UK electricity system. The value of aggregation in reducing price volatility is particularly large when there are many renewables, but storage capacity is relatively low.

If aggregation reduces total system costs more than decentralized coordination, it means there is a disparity between system and private benefits from storage. The income from centralized coordination would be shared between the aggregator and the consumer. Market structures would have to be designed so the aggregator's payment to the consumer would be larger than the consumer would receive from decentralized coordination (i.e. so the export price for consumers using decentralized coordination would be chosen to reflect its lower value to the wider electricity system).

If consumers were willing to allow aggregation they would likely enable a lower electricity price for all consumers, but their technology's private value would reduce. Our analysis suggests that load-reflective payments directed from the aggregator to each consumer, which considers individuals' utilization of storage, could be sufficient to nudge consumers into maximizing system rather than private benefits, and will depend on how costs are allocated through tariffs. This framework could provide a foundation for subsidies targeting storage, at least initially, which may facilitate the removal of market barriers (Castagneto Gissey et al., 2017a) that impede storage deployments in the electricity system.

In a competitive market with full cost pass-through to the 27.6 m UK customers (BEIS, 2017), assuming evenly distributed electricity bills around a mean of £ 554 (Ofgem, 2017), the electricity system could expect to lose up to 407 £m/year in the absence of centralized coordination of consumers' energy storage. Our work confirms and extends the findings in Jia and Tong (2016), who found welfare-enhancing benefits of centralizing demand-side scheduling, and those of He et al. (2012), who found that centralized coordination leads to lower supply costs than private operation. It enhances the literature by quantifying the impact of coordination on electricity price levels and variability using a whole-systems approach, which is necessary to address these questions.

Market structures are a key component of our model. Arguably, if market structures were optimal, then minimizing consumer costs would maximize the contribution of storage to the system. Our study found that the disparity between system and private value from storage and consumers' decentralized energy resources is likely to become more pronounced as the retail price becomes more responsive to the wholesale price. We showed that regulating the retail price mark-up over wholesale costs in a way that it becomes more responsive to wholesale demand and supply could increase the differential between peak and off-peak dynamic tariffs and improve the contribution of storage toward system savings. This could be done by either imposing a degree of sensitivity of electricity tariffs to wholesale market fundamentals, or by improving the flow of information relative to electricity demands and supplies from wholesale producers to retailers, for example by establishing a transparency platform in the form of a dedicated software.

Our work also showed how electricity systems generate electricity prices under centralized and decentralized scheduling when there are different types of consumers. Flexible resources of domestic users have the greatest value due to the users' spiky evening demand profiles, by assumption of the underlying operational costs for generating power. Commercial users display lower load variability, explaining the lower system savings they produce. On the other hand, industrial users typically have flat demands so the contribution of their storage resources toward system savings is much lower. These insights could be used to design compensation mechanisms rewarding users for the flexibility they can offer to the wider electricity system.

Yet how consumers can be incentivized to allow system-optimal aggregation, rather than maximizing their private benefit, is a key question. One option would be for aggregators to offer a flexibility payment in exchange for the right to coordinate consumers' flexible resources. These would be similar in nature to air conditioner use mitigation policies in Florida. Similar programs depend on the introduction of advanced metering infrastructure and are designed to help electricity providers save money through reductions in peak demand and wholesale prices.

4.2. Value of consumer storage resources to the electricity system

The utility of storage to the electricity system could depend on aggregators' ability to entice consumers with different load profiles in foregoing control of their technology to benefit the system. Our work suggests that it is possible to design payments for consumers to access these benefits, and that, if appropriately designed, they could help reduce electricity operational costs to all consumers. Such activities necessitate substantial control of consumer assets by aggregators and will likely require new market mechanisms that incentivize these resources to participate more freely in markets for flexibility services, including but not limited to arbitrage. Moreover, a market structure that values the flexibility offered by consumers' flexible resources, viewing them as complementing rather than competing with network and generation assets, would also be required to realize the value of decentralized flexible resources to the electricity system (Castagneto Gissey et al., 2017a).

As a sector, domestic users gain the largest savings from storage coordination. This comes as a result of a higher peak-to-trough ratio as compared to the commercial and industrial sectors. We also observe that with demand-dependent retail price mark-ups (M2 and M3), the domestic sector experiences greater savings (Table 2). This was expected since the objective of storage coordination is to ensure load smoothing. It might suggest that domestic storage brings more value to the system. But considering that the size of storage is negatively correlated with its capital cost, it would make more economic sense to install storage in the non-domestic sectors to achieve higher system savings. However, the fact that system demand peaks are currently correlated with the domestic demand peaks means that effective demand smoothing cannot be accomplished without engaging the domestic sector. One way to do so is to use real-time information (e.g. from smart meters), such as time of electricity use and storage charge level. This could establish sharp ad-hoc signals and enable a more efficient operation of resources from the residential sector.

4.3. Regulating the price mark-up to reduce externalities

Efficient pricing structures could make retail tariffs more closely follow wholesale costs. We considered for the first time the disparity between private and system benefits from consumers' storage resources (a negative system externality) and showed that it is likely to widen as the sensitivity of retail tariffs to wholesale prices increases. A mark-up that is less responsive to changes in wholesale fundamentals could tighten the gap between system and private benefits from consumers' storage resources. This would likely increase the peak to off-peak price differential, improving storage-led arbitrage savings.

Regulating the mark-up's sensitivity could both improve savings from storage and increase the disparity between system and private benefits. While retailers already have the incentive to fully reflect wholesale costs into retail tariffs, which is likely to facilitate the accumulation of savings by storage technologies with time-of-use tariffs, simultaneous policies intended to induce a more equitable distribution of cost savings to consumers could be required. This could be achieved by imposing that redistributed savings for each consumer be reflective of the consumer's load and the decreased cost to the electricity system because of that consumer, whilst ensuring traceability and efficiency. With smart meters, consumers' time-of-use and load could be used to derive an associated system-based compensation to be paid back to the consumer in a similar fashion to the way in which ex-post cash-out payments are made to generators in the Balancing Mechanism.

4.4. Evaluation, limitations and future work

An evaluation of our model, provided by the sensitivities reported in Appendix I, confirms the robustness of our results to changes in various parameters. We only considered extreme cases of completely coordinated or uncoordinated scheduling, but partial coordination could be the most appropriate aggregation strategy to maximize the utility of storage, which could be programmed to meet both system and private needs. We simplified each consumer type by assuming a single load profile, so accounting for the variation within each user category would improve our modelling work. Generation costs were specified as relating to short-run operations, hence balancing and additional costs related to physical grid constraints might improve the accuracy of results. While we considered the impact of coordination on wholesale prices, that on delivered prices should be made to depend on capital, fuel and networks costs incurred by each consumer in the system. In this work, the degradation of consumer storage has been considered implicitly, as described in Appendix G. The objective of this study was to demonstrate the trade-off between centralized and distributed coordination and discuss the potential implication of these findings on the value of storage.

5. Conclusions and policy implications

As consumers increase their holdings of renewables and energy storage, it will be crucial to ensure that their operation does not increase electricity prices. We studied how consumer-led (decentralized) and aggregator-led (centralized) coordination affects the level and volatility of electricity prices.

The ability of consumers to control their technologies is shown to be undesirable from a system perspective even with the objective of demand smoothing, leading to 4–7% greater electricity prices. This occurs because of the smaller portfolio of aggregated flexible resources at the disposal of the System Operator under decentralized coordination, which limits its ability to smooth system demand. Electricity price volatility under centralized coordination is typically lower by 2–3% but could be up to 60% lower depending on the ratio of renewables to aggregated storage capacity.

It is unlikely that consumers will allow a system-optimal operation of their technologies unless they are paid a financial incentive that is sufficient to at least equalize the private and system benefits from their technology. We demonstrated that domestic users would require greater payments than industrial and commercial users as system demand peaks are currently correlated with domestic demand peaks. It would make more economic sense to install storage in the non-domestic sector due to economies of scale, but effective demand smoothing cannot be accomplished without engaging the domestic sector. Providing financial incentives to consumers for the flexibility they can offer to the system could largely contribute toward the realization of system value from consumers' storage resources.

Our analysis also showed that the disparity between system and private benefits from decentralized energy resources will likely increase as efficient pricing structures improve the sensitivity of retail tariffs to wholesale fundamentals, implying that tariff regulation could help reduce this disparity, thereby potentially leading to a greater system utility from private technology.

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Appendix

See Figs. A1–A4 and Tables A1–A3

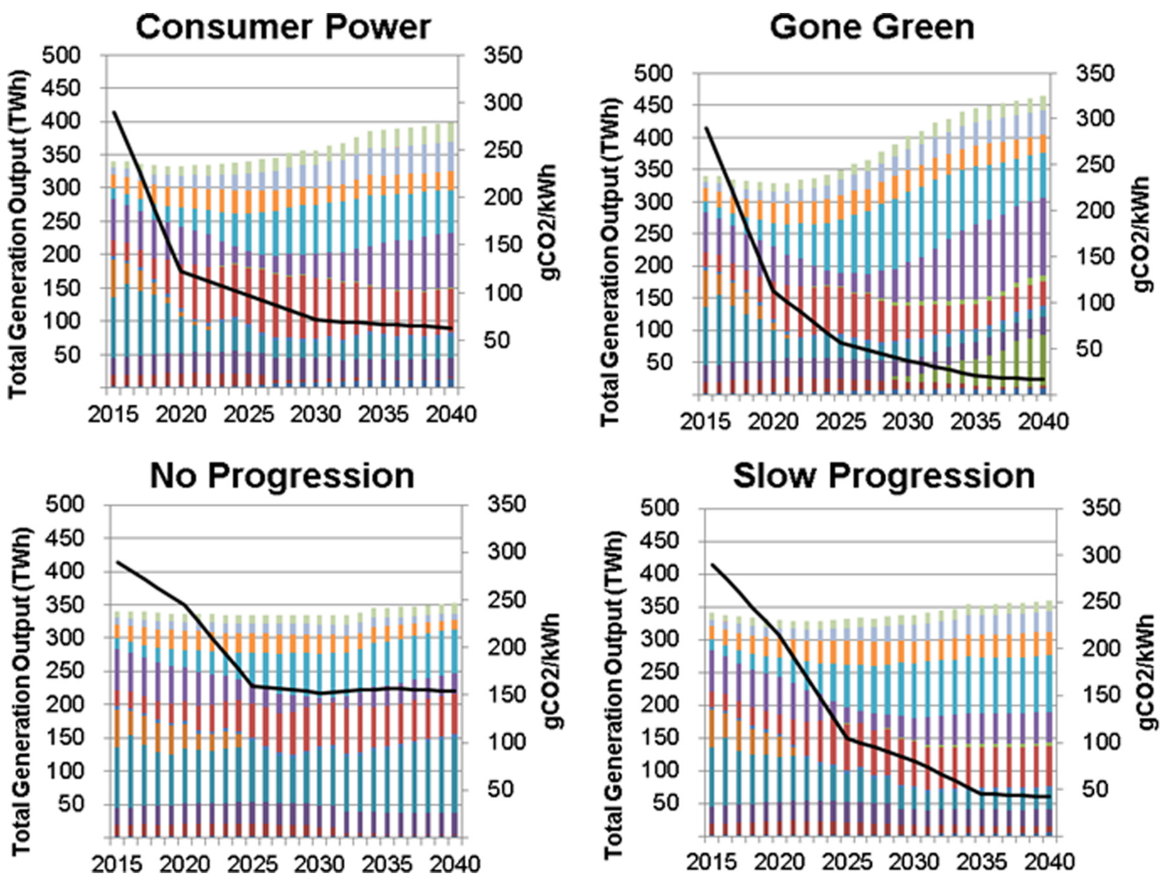

Fig. A1. Electricity generation by National Grid scenario [1].

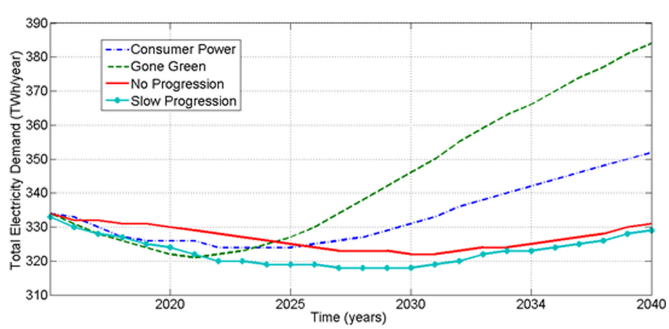

Fig. A2. Electricity demand by National Grid scenario [1].

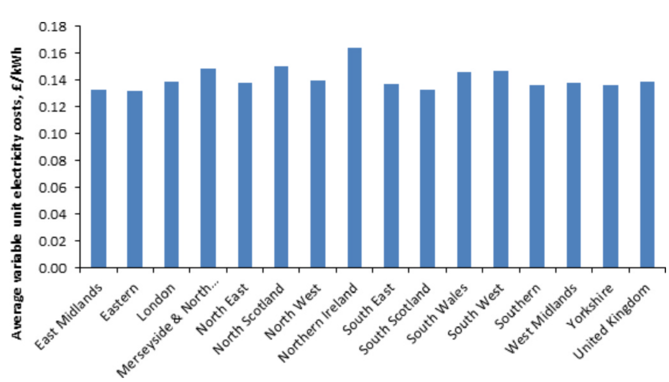

Fig. A3. Average variable unit costs and standing charges for standard electricity in 2015 for UK regions.
Source: [8].

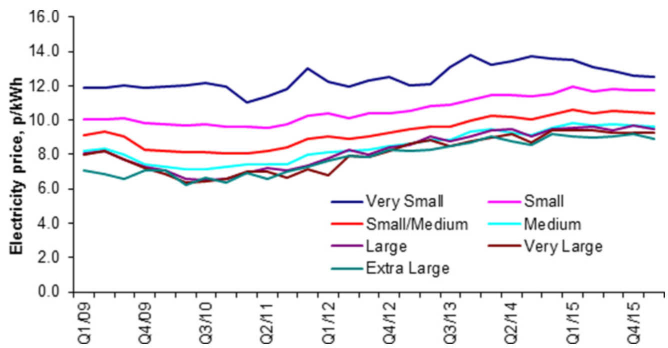

Fig. A4. Prices of purchased electricity by non-domestic consumers.
Source: [8].

Table A1
Model components by type of data used, source of the data, and applied manipulations.

Model component	Data used and source	Data manipulation
Consumer demand profiles	– Daily demand profiles (half-hourly resolution) [9] – Annual energy consumption by sector up to 2040 [1] – Hourly heat demand profiles for domestic sector taken from [10] – Vehicle traffic data [11]	– Daily profiles were aggregated into yearly profiles for different sector and scaled according to annual energy consumption data per sector. – Thermal electricity profiles are calculated by taking the difference between seasonal electricity demand profiles assuming that no heating occurred in the summer. – Number of consumers was calculated to add up to aggregate historical energy consumption values [10] – For transportation demand profile is based on the traffic activity data assuming that if the vehicle is stationary it is charging. This is combined with the data for EV numbers from FES.
Generation	– Installed generation capacities up to 2040 [1] – Fuel and carbon prices up to 2040 [1] – Renewable generation profile [12, 13] – Generator costs provided by UK TIMES-MARKAL-UCL (UKTM-UCL) [14]	– Dispatchable generators – SRMC were calculated for each type of electricity generator according to Eq. A4 and stacked into a merit on hourly basis – Renewable generators – historical generation profiles were scaled according to installed capacities [1] – Solar PV installations were split between sectors according to current shares [4]
Consumer technology and storage	– Installed storage capacities for pump and consumer electrical storage up to 2040 [1] – Heat pumps capacities [1, 15] are assumed to increase at the same rate as in the domestic sector as stated in the FES [1]	– Thermal storage capacity was based on domestic values for 2015 and scaled in line with electrical storage for all sectors [3] – Capacities of heat pump, storage and electric vehicles were adjusted in order to add up to aggregate energy consumption values published in FES [1]
Prices	– Consumer retail prices [7] – Non-domestic electricity prices [8]	– Retail price uplift was calibrated against historical retail prices [7, 8]
Environment	– External temperature [5]	– Used for COP calculations in Eq. A8

Table A2
Technical model details and data used in this study's modelling exercise.

Model parameter	Value
Number of consumers in 2015: domestic, commercial, industrial	25378 thousand, 4699 thousand, 809 thousand
Efficiencies: η_{ES}, η_{TES}, η_{EV}, η_{HP}	0.8,0.8,0.8,0.8, 0.4
Minimum power operation capacity: l_{HP}^{min}, l_{ES}^{min}, l_{EV}^{min}, l_{pump}^{min}	0 for all
Minimum storage state of charge: E_{ES}^{min}, E_{TES}^{min}, E_{EV}^{min}, E_{pump}^{min}	0% for all
Maximum storage state of charge: E_{ES}^{max}, E_{TES}^{max}, E_{EV}^{max}, E_{pump}^{max}	100%
Heat pump capacity across sectors: domestic, commercial, transport	431MWh, 639MWh,668MWh

Table A3
Sensitivity analysis. Impact of key variables on electricity system savings.

Coordination	Distributed		Centralized	
Variable	Change in electricity system savings per unit of storage capacity (%) for a 33% increase in variable	Change in electricity system savings per unit of storage capacity (%) for a 33% decrease in variable	Change in electricity system savings per unit of storage capacity (%) for a 33% increase in variable	Change in electricity system savings per unit of storage capacity (%) for a 33% decrease in variable
Default savings	403 [£ /MWh/year]	403 [£ /MWh/year]	3832 [£ /MWh/year]	3832 [£ /MWh/year]
Demand	1310.95%	− 156.79%	306.06%	− 30.60%
Gas price	− 2.38%	87.66%	14.86%	− 3.68%
Gas capacity	− 152.15%	712.74%	− 28.03%	152.26%
Coal price	31.96%	− 21.05%	7.26%	− 5.19%
Coal capacity	− 102.07%	193.04%	− 18.37%	38.92%
EV capacity	− 18.00%	10.14%	0.04%	− 0.04%
Wind capacity	− 40.28%	67.36%	− 7.19%	11.97%
Solar capacity	− 0.83%	2.71%	− 1.44%	2.36%
Thermal storage capacity	7.44%	− 21.26%	− 18.36%	30.25%
HP capacity	327.86%	− 134.71%	86.59%	− 46.95%
Consumer electric storage capacity	− 10.25%	0.69%	− 0.68%	0.69%
System storage	− 14.49%	15.64%	− 5.53%	5.99%
Carbon price	44.91%	− 11.92%	13.41%	− 9.93%

Appendix A. Supporting information

Supplementary data associated with this article can be found in the online version at doi:10.1016/j.enpol.2019.01.037

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