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Impact of Household Heterogeneity on Community Energy Storage in the UK

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Abstract

The increasing penetration of Decentralised Energy Resources (DERs) into the residential sector along with a reduction in their subsidy in many countries requires innovative approaches to ensure economic viability. Whilst applications of Household Energy Storage (HES) have been widely investigated and deployed, in recent years communities have been identified as a key scale for energy systems, particularly for energy storage. Community Energy Storage (CES) is therefore a promising alternative deployment model to assist the roll-out of DERs. The power and energy demand may vary significantly with the demographic composition of community; therefore, it is important to evaluate the operation of HES and CES for different communities and hence to assign suitable energy storage options to corresponding objectives. In this work, an Agent Based Model (ABM) is developed that includes household demand heterogeneities, as well as HES and CES, and photovoltaic (PV) systems. The single household models can be aggregated to a community, and hence it is able to simulate the interaction between households in a local, grid connected, energy system. A battery degradation model is also included in order to reproduce the capacity fade of a Li-ion battery over time. The impact on battery performance of the heterogeneous demand within communities is explored using typical performance indicators, such as Self-Consumption Rate (SCR), Self-Sufficiency Rate (SSR) and battery cycle counts.

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Keywords: Photovoltaics; Lithium-ion battery; Agent-based modelling; Energy system simulation; Community Energy Storage

1. Introduction

In the past decade, the growing energy demand [1] and pressing need to mitigate greenhouse gases emissions [2] have contributed to a significant global transition from carbon-intensive energy sources to clean sources of energy, accelerating the adoption of renewable energy in our energy mix, especially solar energy [3,4]. Energy storage is

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an ideal supplement for solar because of its intermittent nature and is expected to play an important role in future. The retail costs of PV and storage systems has reduced remarkably in the last few years, providing further impetus and opportunities for their deployment [5]. Significant uptake of PV plus storage units is now considered a possible pathway to distributed energy systems, which will lead to higher local self-consumption level. These systems have been extensively adopted and investigated at residential level [6–9]. Although PV plus household energy storage (HES) can reduce reliance on the grid, most literature has found it economic feasibility to be an issue [9–13]. It is therefore of great importance to look for other sustainable operating strategies, especially after the closure of relevant subsidies [14].

Community Energy Storage (CES) is located at the consumption level and is capable of performing multiple useful applications for both consumer and the Distribution Network Operators (DNOs), such as increasing self-consumption and peak shaving [15]. Many studies have found CES to provide additional benefits compared to HES, in terms of economies of scale, energy trading and enhanced grid balancing capabilities [16–18]. With increased electrification of heating and transport, the UK will see a drastic change in energy demand [19,20], especially after significant growth in uptake of PV. Instead of managing PV power flow within a single household using HES, CES is found to result in less customer involvement but with higher efficiencies and less loss from charging, discharging and self-discharge [21]. A CES network may be able to localize more energy demand within a community due to its higher capacity and hence reduce reliance on the external grid. However, literature lacks relevant understanding of what types of communities are suitable for CES applications and how the community heterogeneity will influence the operation of a CES system.

This study aims to investigate how demand heterogeneity influences the usage of on-site PV production and the operation and performance of the CES. In addition, this study investigates how the battery lifetime varies with this same community heterogeneity. The paper is arranged as follows: Section 2 presents the methodology used in the study, including the model set-up and evaluation criteria. Section 3 presents and also discusses the results from simulations. Section 4 concludes the findings of this study.

2. Methodology

To analyse the impact of demand heterogeneity on system performance, an agent-based model is proposed. The development of the agent-based framework is based on an AC-coupled domestic PV system, as described in [13]. For this study, the model structure is updated to include a supply/demand model that consists of 10 household agents, where each household may have different demand and needs from the external grid. The engineering models represent the physical technologies that each agent contains. Agents are able to interact with each other following the pre-set rules to determine the individual and overall system behaviour.

2.1. Model setup

Fig. 1 illustrates the structure of the households and community in this study, each being represented by a household/community agent in the model. Each household agent consists of 3-kWp PV, a DC/AC converter,

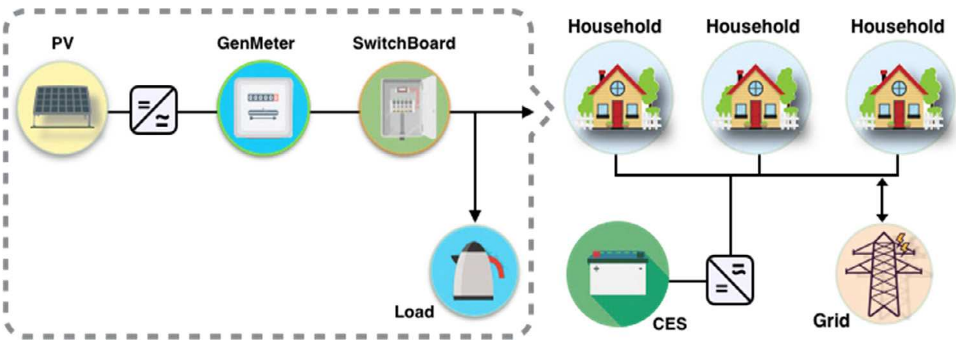

Fig. 1. System set-up of case 3: PV+CES.

generation metre, household demand and the grid. All 10 households are assumed to have the same PV panel specifications and PV generation profiles, regardless of their tilt angle and direction the PV panel faces. The CES is a collective asset owned by the households connected to the CES. Additionally, the CES network within the community is also assumed to be private and there are no other charges during use apart from a one-off payment to DNO for retrofitting network capacity [22]. The CES system consists of batteries and a CES management (CESM). As investigated in [13], most residential users in the UK have installed a 3-kWp PV panel coupled with a 3-kWh HES. In this study, we assume the community to have the same total capacity for the CES, 30 kWh. The AC-DC inverters are assumed to have efficient conversion rate, around 95%. The CESM controls the dispatch of power flow between the households, CES and the grid. More detail about the CESM is given in Section 2.4.

2.2. Household and community demand

Household demand profiles are derived from a demand model developed by [23]. Five different demands are adapted in order to represents Low to High energy consumption bands according to Ofgem's Typical Domestic Consumption Values [24] described in [13]. In order to investigate the impact of community demand heterogeneity, 12 communities are considered. Both the highest possible and lowest possible community demands are modelled (i.e. 10 houses each with the highest demand and 10 houses each with the lowest demand respectively). The remaining 10 communities modelled each have 10 houses with randomly allocated load profiles. The average monthly consumptions are shown in Fig. 2, with the error bars representing the highest and lowest demand cases.

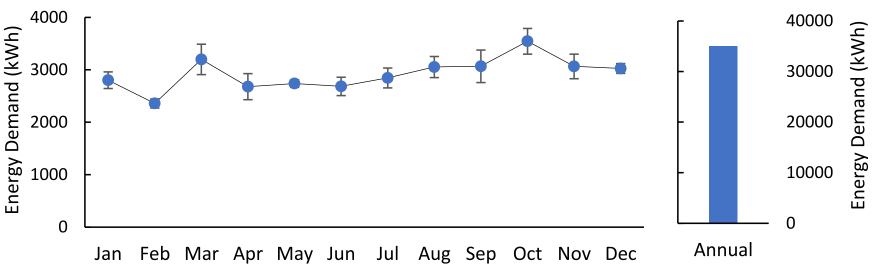

Fig. 2. Monthly and annual energy consumption of a community.

2.3. PV generation

The on-site electricity generation is produced by a 3 kWp rooftop PV panel based on the weather data measured in the Sheffield area. The historic irradiance and weather dataset is obtained from the Microgen Databased developed by Sheffield Solar [25]. The monthly and annual solar generation of a community is presented in Fig. 3.

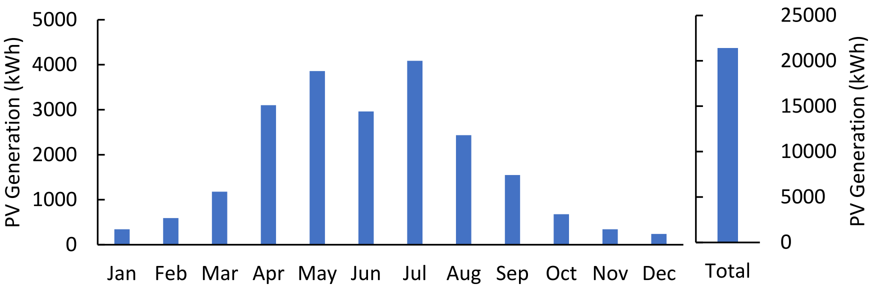

Fig. 3. Monthly and annual energy PV generation of a community.

2.4. CES and CES management (CESM)

The CES is installed near the grid connection point and the CESM calculates the total demand and total generation at each time step (1 min) in order to meet the energy balance; therefore, power balance is an important parameter for the CES to determine its charging and discharging process, i.e.:

$$P_{PV} = P_{DSC} + P_{Nbr\_Sharing} + P_{charge} + P_{export} \quad (1)$$

$$P_{demand} = P_{DSC} + P_{Nbr\_Shared} + P_{discharge} + P_{import} \quad (2)$$

where P_{pv} is the PV power (kW), P_{DSC} is the directly self-consumed PV power (kW), P_{charge} is the battery charging power (kW), P_{export} is power exported to the grid (kW), P_{demand} is the household demand (kW), P_{Nbr_Shared} is the power imported from neighbours (kW), $P_{Nbr\_sharing}$ is the power exported to neighbours (kW), $P_{discharge}$ is the battery discharging power (kW), and P_{import} is the power import from the grid (kW). In this work, a battery degradation model is developed and introduced to the community model. In order to obtain the number of duty cycles of the storage unit, the calculation is based on the energy input and output, shown in Eq. (3). The battery capacity loss can then be formulated into a relation between the number of battery duty cycles, depth of discharge (DOD) and battery capacity loss percentage, as developed by [26].

$$Number\ of\ Cycles = Total\ Energy\ Output/(DOD \times Battery\ Capacity) \quad (3)$$

2.5. Evaluation criteria

Some key performance indicators are introduced to this technical assessment, including self-consumption rate (SCR), self-sufficiency rate (SSR), number of cycles of the CES, and the CES capacity loss (%). The SCR represent the fraction of self-consumed PV electricity over the total PV generation, while the SSR is the proportion of self-consumed PV electricity in the total demand. The addition of storage system might cause some discrepancies due to the amount of energy left in the battery and the electricity shared with/from other neighbours [27]. In this way, new definitions of SCR and SSR are used in this research are shown in Eqs. (4) and (5):

$$SCR = \frac{E_{PV} - E_{export}}{E_{PV}} \quad (4)$$

$$SSR = \frac{E_{demand} - E_{import}}{E_{demand}} \quad (5)$$

where the E_{pv} is the amount of electricity generated on-site (kWh), E_{export} is the amount of energy exported to the grid (kWh), E_{demand} is the total community energy demand (kWh), and E_{import} is the energy import from the grid (kWh).

3. Results and discussion

3.1. Impact of demand heterogeneity on community energy storage

Fig. 4(a) shows the average SCR of the 12 simulated communities. The SCR is significantly influenced by the season changes rather than demand heterogeneities, where warmer months contribute to lower SCR and colder months lead to a higher SCR. Although the community demand in some months in Fig. 2 has significant variation due to heterogeneity, such as September, the average SCR of the community remains very high, around 97%. For the months where the demand is significantly smaller or larger than the PV production, community demand heterogeneity is found to be less influential to the community SCR. However, when the monthly demand is similar to PV production, such as June, a demand changes up to 350 kWh leads to a 6% SCR variation. Across the whole year, the demand heterogeneity leads to a decrease in annual average SCR ranging from 74% to 68%, which is not a significant change for a 10-house community with a 30 kWh CES, but it could be for a bigger community.

Fig. 4(b) shows the average SSR of the communities with various demands. As with Fig. 4(a), the variation of SSR through the year clearly shows that seasonal changes play a more important role. This mirrors the tendency of monthly PV production over a year, suggesting the increasing PV production contributes to more community demand met by PV energy. Comparing Figs. 2 and 3, in winter the difference between demand and PV production is so great that the demand variation to contribute to any obvious change in SSR, while in summer the change in SSR is more obvious and a 6% variation can be achieved. Across the whole year, for a community with an average consumption at 35 065 kWh and SSR at 40%, a demand variation ranging up to 3258 kWh can lead to a

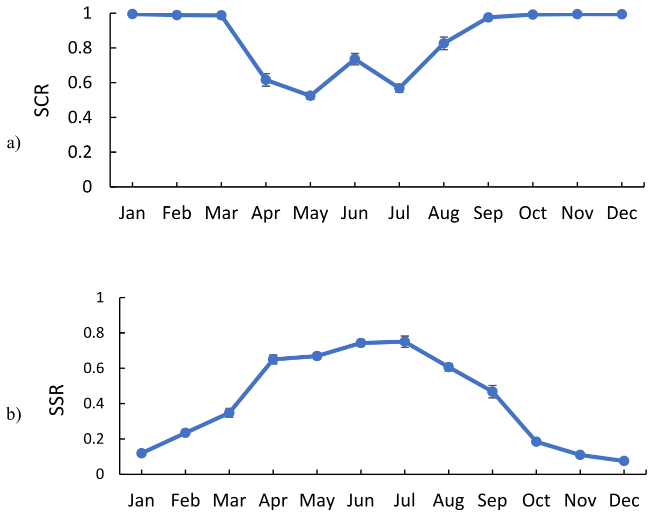

Fig. 4. Community demand heterogeneity impact on (a) SCR and (b) SSR.

7% variation in SSR. As mentioned previously, the SSR of a community is determined by the community demand, but the demand heterogeneity does not lead to any obvious variation.

The results in Section 3 have shown that community demand heterogeneity can lead to some changes in energy localization within the community and also CES performance, especially when demand and PV production are similar. In contrast, demand heterogeneity is found to be insignificant when the demand remarkably differs from PV production, as the variation cannot make any drastic improvement in the utilization of the PV energy. Our results match the trend discovered by other researchers [28], as different types of demand profiles have little influence on CES system performance, but they are meaningful for system planning.

3.2. Impact of demand heterogeneity on the use of CES

Fig. 5 shows the average monthly CES duty cycle over a year, which follows the trend of community SSR demonstrated previously. Demand heterogeneity is found to have insignificant impact on the CES performance, which leads to a negligible change in the number of CES duty cycles. In contrast, the CES operation is heavily reliant upon season changes. Due to the CES is only used to charge surplus PV electricity, the duty cycles of the CES increases with the total PV surplus production. The CES can finish a full charging/discharging cycle from April to August, and during simulation sometimes two full cycles can be achieved within a day. However, in winter months the average number of cycles is below 10. Across the whole year, the average CES duty cycle is ca. 217 cycles with a range from 200 to 250, and correspondingly the capacity of a brand-new CES is found to have a degradation at around 3%–4% per year based on the total energy output.

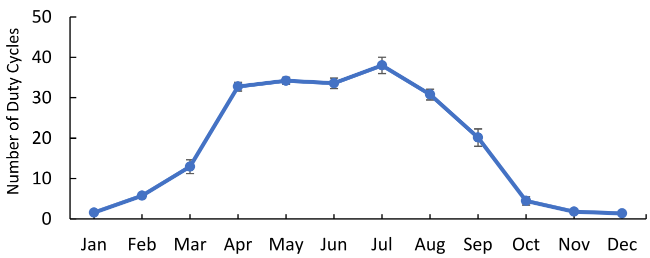

Fig. 5. Impact of community demand on the CES.

Although community demand variation can change the use of the battery, our results find that the change in the number of CES duty cycles looks unlikely to cause any significant capacity degradation of the CES, compared to an average at 4000 full cycles across a lithium-ion battery's lifespan [29]. However, most empirical battery degradation models are tailored for a specific battery application, where the battery operation region is narrow so that a satisfactory accuracy can be achieved. Our model is adapted from a battery cell model developed by [26], of which the battery operation pattern will be different from that of CES system. In this way, the battery degradation model in our study still needs further validation by comparison with real data.

4. Conclusion

An agent-based model is presented in this paper and used for our investigation in the impact of community demand heterogeneity. The results show that the change in community demand looks insignificant to the overall SCR and SSR of the community, though it can cause some impacts on energy localization and the use of PV power. In addition, the community demand variation can cause influences on the use of CES, but it is found unlikely to lead to significant CES capacity degradation.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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