

Modeling economic sharing of joint assets in community energy projects under LV network constraints

Norbu, Sonam; Couraud, Benoit; Robu, Valentin; Andoni, Merlinda; Flynn, David

DOI

[10.1109/ACCESS.2021.3103480](https://doi.org/10.1109/ACCESS.2021.3103480)

Publication date

2021

Document Version

Final published version

Published in

IEEE Access

Citation (APA)

Norbu, S., Couraud, B., Robu, V., Andoni, M., & Flynn, D. (2021). Modeling economic sharing of joint assets in community energy projects under LV network constraints. *IEEE Access*, 9, 112019-112042. [9508959]. <https://doi.org/10.1109/ACCESS.2021.3103480>

Important note

To cite this publication, please use the final published version (if applicable). Please check the document version above.

Copyright

Other than for strictly personal use, it is not permitted to download, forward or distribute the text or part of it, without the consent of the author(s) and/or copyright holder(s), unless the work is under an open content license such as Creative Commons.

Takedown policy

Please contact us and provide details if you believe this document breaches copyrights. We will remove access to the work immediately and investigate your claim.

Received July 15, 2021, accepted August 4, 2021, date of publication August 9, 2021, date of current version August 17, 2021.

Digital Object Identifier 10.1109/ACCESS.2021.3103480

Modeling Economic Sharing of Joint Assets in Community Energy Projects Under LV Network Constraints

SONAM NORBU^{1,2}, (Member, IEEE), BENOIT COURAUD¹, (Member, IEEE),
VALENTIN ROBU^{1,3,4}, MERLINDA ANDONI¹, (Member, IEEE),
AND DAVID FLYNN¹, (Member, IEEE)

¹Smart Systems Group, School of Engineering and Physical Sciences, Heriot-Watt University, Edinburgh EH14 4AS, U.K.

²Centre for Renewable and Sustainable Energy Development (CRSED), Electrical Engineering Department, College of Science and Technology, Royal University of Bhutan, Phuentsholing 21101, Bhutan

³Centre for Mathematics and Computer Science (CWI), Intelligent and Autonomous Systems Group, 1098 XG Amsterdam, The Netherlands

⁴Algorithmics Group, Faculty of Electrical Engineering, Mathematics and Computer Science (EEMCS), Delft University of Technology (TU Delft), 2628 XE Delft, The Netherlands

Corresponding author: Sonam Norbu (sn51@hw.ac.uk)

This work was supported in part by U.K. Engineering and Physical Sciences Council (EPSRC) Doctoral Training Programme (DTP) under Grant EP/R513040/1, in part by the EPSRC through U.K. National Centre for Energy Systems Integration (CESI) under Grant EP/P001173/1, in part by the Community—Scale Energy Demand Reduction in India (CEDRI) under Grant EP/R008655/1, and in part by the Innovate U.K. Responsive Flexibility (ReFLEX) under Project 104780.

ABSTRACT The trend of decentralization of energy services has given rise to community energy systems. These energy communities aim to maximize the self-consumption of local renewable energy generated and stored in assets that are typically connected to low-voltage (LV) distribution networks. Energy community schemes often involve jointly owned assets such as community-owned solar photo-voltaic panels (PVs), wind turbines and/or shared battery storage. This raises the question of how these assets should be controlled in real-time, and how the energy outputs from these jointly owned assets should be shared fairly among heterogeneous community members. Crucially, such real-time control and fair sharing of energy must also consider the technical constraints of the community, such as the local LV network characteristics, voltage limits and power ratings of electric cables and transformers. In this paper, we design and analyze a heuristic-based battery control algorithm that considers the influence of battery life degradation, and the resultant increase in local renewable energy consumption within local operating constraints of the LV network. We provide a model that first studies the techno-economic benefits of community-owned versus individually-owned energy assets considering the network/grid constraints. Then, using the methodology and principles from cooperative game theory, we propose a redistribution model for benefits in a community based on the marginal contribution of each household. The results from our study demonstrate that the redistribution mechanism is fairer and computationally tractable compared to the existing state-of-the-art methods. Thus, our methodology is more scalable with respect to modeling the economic sharing of joint assets in community energy systems.

INDEX TERMS Battery degradation model, coalitional game theory, community energy storage, community vs. individual energy assets, energy community, energy sharing mechanism, low-voltage network, network constraints, self-consumption.

NOMENCLATURE

SUBSCRIPTS AND SETS

i for agents (households)
 \mathcal{C} for community

The associate editor coordinating the review of this manuscript and approving it for publication was Salvatore Favuzza¹.

N set of the number of agents (households)
 T set of the number of time periods

PARAMETERS

η^c battery charging efficiency
 η^d battery discharging efficiency
 SoC^{initial} initial battery SoC [%]

SoC^{\max}	maximum battery SoC [%]
SoC^{\min}	minimum battery SoC [%]
DoD	battery depth of discharge [%]
$p^{\text{bat,max}}$	maximum power that battery can charge/discharge [kW]
$V^{\text{slack bus}}$	voltage of the slack/reference bus [V]
$p^{\text{curtailed}}$	curtailed power i.e curtailment of export from renewable generator (solar PV/wind turbine), or curtailment of export/import from/to battery [kW]
$\tau^s(t)$	selling price (export tariff) at t [pence/kWh]
$\tau^b(t)$	buying price (import tariff) at t [pence/kWh]
$c_i^A(T)$	annualized cost of the asset for agent i , where $T = 1$ year [£/kWh for battery, and £/kW for solar PV/wind turbine]
$c_C^A(T)$	annualized cost of the asset for community C , where $T = 1$ year [£/kWh for battery, and £/kW for solar PV/wind turbine]

VARIABLES

t	time period
Δt	duration of the time period t
$SoC(t)$	battery state of charge at t [%]
DF^{regular}	depreciation factor due to regular cycle
$DF^{\text{irregular}}$	depreciation factor due to irregular cycle
$V^{\text{bus}}(t)$	bus voltage at t [V]
$P^{\text{bus}}(t)$	bus power at t [kW]
$g_i^{\text{wind/solar}}(t)$	power from the renewable generator of agent i at t [kW]
$g_C^{\text{wind/solar}}(t)$	power from the renewable generator of community C at t [kW]
$p_i^{\text{grid}}(t)$	power from the utility grid of agent i at t [kW]
$p_C^{\text{grid}}(t)$	power from the utility grid of community C at t [kW]
$p_i^{\text{bat}}(t)$	power of the battery for agent i at t [kW], charging(-ve) and discharging(+ve)
$p_C^{\text{bat}}(t)$	power of the battery for community C at t [kW], charging(-ve) and discharging(+ve)
$d_i(t)$	power consumed by the agent i at t [kW]
$d_C(t)$	power consumed by the community C at t [kW]
$e_i^s(t)$	energy exported by agent i at t [kWh]
$e_C^s(t)$	energy exported by community C at t [kWh]
$e_i^b(t)$	energy imported by agent i at t [kWh]
$e_C^b(t)$	energy imported by community C at t [kWh]
$b_i(T)$	annual bill for agent i , where $T = 1$ year [£]
$b_i^0(T)$	baseline annual bill for agent i without any assets, where $T = 1$ year [£]
$b_i^*(T)$	new annual bill for agent i after redistribution of savings, where $T = 1$ year [£]
$b_i^{*(-)}(T)$	new annual bill for agent i after redistribution of savings without network constraints, where $T = 1$ year [£]

$b_i^{*(NC)}(T)$	new annual bill for agent i after redistribution of savings with network constraints, where $T = 1$ year [£]
$b_C(T)$	annual bill for community C , where $T = 1$ year [£]
$b_C^{NC}(T)$	annual bill for community C with network constraints, where $T = 1$ year [£]
$b_C^-(T)$	annual bill for community C without network constraints, where $T = 1$ year [£]
$\Pi_C(T)$	saving of the community C after 1 year ($T = 1$ year) [£]
$\Theta_i(T)$	marginal contribution of an agent i [£]
$I_i(T)$	benefits redistributed to agent i after period T [£]

ABBREVIATIONS

ANM	Active Network Management
BESS	Battery Energy Storage System
CES	Community Energy Storage
DERs	Distributed Energy Resources
DF	Depreciation Factor
DNOs	Distribution Network Operators
DoD	Depth of Discharge
DSM	Demand Side Management
DSO	Distribution System Operator
EoL	End of Life
FITs	Feed-in Tariffs
HES	Household Energy Storage
LACE	Levelized Avoided Cost of Electricity
LCOE	Levelized Cost of Electricity
LV	Low Voltage
MIDAS	UK Met Office Integrated Data Archive System
P2P	Peer-to-Peer
ReFLEX	Responsive Flexibility
RES	Renewable Energy Sources
SCR	Self Consumption Rate
SoC	State of Charge
SRR	Self Sufficiency Rate
ToU	Time of Use

I. INTRODUCTION

Access to affordable renewable energy resources (RES) represents a key element of an inclusive energy transition, represented as one of the core UN sustainable development goals [1]. Enhancing the use of locally-generated renewable energy can reduce the energy system contribution to climate change [2], achieve decarbonizations [3], and speed up the transition to a low carbon economy [4]. This has led to an exponential growth in the deployment of RES. The increasing number of distributed energy resources (DERs) connected to LV distribution networks is shifting the development of energy systems towards a more decentralized structure, enabling a significant shift in market power from large producers to individual prosumers [5].

However, the increase in penetration of distributed generation results in new challenges for the operation of distribution networks. A key challenge with RES generators is that they are intermittent, small-sized and distributed across the distribution network. They are gradually transforming networks into active and two-way energy flow networks, crucially challenging the way they are traditionally designed and managed. For instance, power flows become reversed and the distribution network is no longer a passive circuit supplying loads but becomes an active system with power flows and voltages determined by the local embedded generation output as well as the loads [6]. Voltage out-of-bounds excursions (i.e. temporary fluctuations of voltage outside safe accepted limits, often determined by regulation) are an example of the new challenges for the distribution system operators (DSOs) face when managing the network in real-time.

In addition to the challenges faced by DSOs, the increasing electricity retail prices and decreasing feed-in tariff rates have reduced the incentives for household and business consumers to invest in distributed renewable energy sources. Still, the energy transition that has started in many countries requires households to keep investing in renewable energy generation. This has led to the emergence of local or community energy systems where household and business prosumers aim to maximize behind-the-meter self-consumption from local renewable generation to make DERs more profitable [7]. An energy community is made up of a number of individual prosumers connected to a low-voltage distribution network, usually behind the same primary sub-station. Prosumer assets (i.e. renewable generation capacity and storage) can be either distributed at individual households or centrally installed and thus shared within the community. Hence, this requires new control techniques for the optimization of self-consumption in energy community microgrids subjected to physical network and operational constraints [8]. Therefore, there is an increasing interest from academia and industry in designing, analysing and assessing the community energy schemes, against criteria such as scalability, efficiency and resiliency.

Recently, several community energy projects have emerged in the UK, the EU and worldwide. For instance, In the UK, Community Energy Scotland (a key local organization supporting the development community energy projects) lists more than 300 community energy projects on their website [9]. Similar rising trends in smart energy community initiatives can be seen across the United States (such as the Brooklyn Microgrid project [10]), and across Europe (refer [11] for an overview).

A crucial aspect of a community energy models and projects is that they often involves sharing of some joint resources and assets. One approach is to facilitate peer-to-peer (P2P) trading in the case of individually-owned assets, whereas another approach consists in creating a community energy coalition in the case of community-owned assets, where an aggregator or community energy operator distributes the benefits within the community. A successful

example of such a scheme is the “Ecovillage” of Findhorn in Scotland, UK [12]. Despite the fact that number of energy communities has witnessed a rapid increase, there is still a considerable gap in both existing research and practice regarding what are the optimal and fair methods to redistribute the energy outputs (and hence financial benefits) from the jointly community-owned assets to their members.

The physical network (the LV distribution grid) is an essential entity that allows the exchange of energy in the settings of the energy communities. However, an important aspect that has often been neglected in existing research on energy community models is the relevance of the distribution grid’s technical limits. Installation of renewable generator (solar PV/wind turbine) or batteries in the grid changes power flows, and might create congestions, voltage excursions, or line over-heating. In such cases, the grid operator might consider the need for an Active Network Management (ANM) to remotely control the injection of distributed renewable generator and storage assets. Therefore, due to this congestion/voltage excursion, assets might be prevented from exporting/consuming to/from the grid, reducing the benefits from their owners. For instance, when the grid is constrained with voltage excursions, then the exports from PV/wind turbine and exports/imports from/to battery can be curtailed as it is currently the case in Orkney Islands [13], UK. Therefore, such curtailment events need to be accounted for in the energy community setting by including power flow (physical network/grid constraints) in the techno-economic analysis. For example, in most of the prior literature, the studied models of energy communities do not consider the impact of physical network constraints in the assessment of the techno-economic benefits of community-owned energy assets compared to individually-owned energy assets.

Furthermore, although most prior literature sources show that community-owned battery storage system offers higher benefits as compared to individually-owned distributed batteries [7], [14]–[17], these studies often do not consider battery degradation cost. Also, although higher benefits can be achieved by investing in community assets, how to redistribute these benefits among the individual households in the community still remains a key open question, of both research and practical interest. Current energy communities usually employ algorithms based on proportionality of consumption to redistribute the benefits from the community-owned generator assets. However, such methods are not fair, and not applicable in the case of energy storage assets, where the proportionality of the asset usage does not apply. Hence, there is a need to design an efficient and fair redistribution mechanisms that applies to both community-owned renewable generator and storage assets, while incorporating the asset’s degradation, and the physical network and operational constraints.

In this paper, to address the above challenges, we propose a model that first studies the techno-economic benefits of community-owned assets versus individually-owned energy assets considering the network/grid constraints. In order to

assess the benefits from installing various assets including a comprehensive model of battery degradation, we propose an approach based on real time-series data of a community, and compare the benefits provided by community-owned assets with the benefits expected from individually-owned assets, considering operational network constraints. Then, using the methodology and principles from cooperative game theory [18], we propose a redistribution model for benefits in a community based on marginal value, a key concept in cooperative (or coalitional) game theory.

In the context of decentralized energy systems, coalitional game theory has been identified as a promising solution for designing incentive mechanisms for community energy trading and sharing. In a cooperative game, players form coalitions to maximise a common objective for mutual benefit. Then, the benefit is distributed equally or fairly among themselves using incentive-based solution concepts, such as the Shapley value. Existing coalitional game theory redistribution mechanism based on concepts like the Shapley value use marginal contributions at their core, but present issues of scalability as the number of agents in a coalition increases [19], [20]. Moreover, most of existing redistribution frameworks are developed without considering network constraints, in which case the computation cost becomes even more challenging. To address this computational challenge, we propose in this paper a more computationally tractable (and hence more practically applicable) redistribution mechanism based on the marginal contribution of each agent (in our case household) of the community. In detail, the main contribution of the paper can be summarized as follows:

- We provide a techno-economic comparison between two configurations of energy communities connected to a low-voltage distribution network. First, a configuration with individually-owned distributed energy assets, such as solar PV and residential batteries. Then, a second configuration in which distributed energy assets are jointly owned by the community, and installed in a single location. The proposed two configurations of energy communities are compared by studying the economic impacts of installing various energy assets on the grid for both fixed and dynamic time of use (ToU) tariffs.
- We incorporate power flow (physical network/grid constraints), and physical battery degradation into community energy optimization models, including the effect of network constraints on redistribution schemes. To achieve this, we employ a battery state of health degradation model based on the battery depth of discharge in each control cycle, while maintaining the bus voltages within the permissible limits. This represents a considerable extension of prior work of control and sharing of assets in energy communities, which do not – or very rarely consider physical LV network constraints in their modeling (including the model in the authors' own prior work [21])
- We investigate and propose a fair and computationally tractable redistribution scheme for sharing the benefits

obtained from community-owned energy assets subjected to physical network constraints, based on principles from cooperative game [18], [19], and test its advantageous by comparing with the state-of-the-art redistribution mechanism.

- The proposed energy community model is validated using a real case study from the ReFLEX (Responsive Flexibility) project that aims to develop a large-scale demonstrator for community energy integration in Orkney, Scotland, UK [22].

The remainder of the paper is structured as follows: Section II discusses relevant literature on state-of-the-art research that models energy communities and state-of-the-art approaches for redistribution benefits from community owned assets. Energy community network modeling along with battery and voltage control mechanism, assessment of energy community efficiency, and mechanism for fair redistribution of benefits from community-owned assets to individual households methodologies are presented in Section III. Results of the techno-economic analysis of community-owned assets versus individually-owned assets, and the various redistribution schemes of benefits achieved from community assets are presented in Section IV. Finally, Section V concludes and elaborates on future work.

II. RELATED WORK

A. STATE OF ART IN ENERGY COMMUNITY MODELING

Energy community schemes are a fast-growing area of research that have gained increased attention in the literature. For instance, the relevant literature identified using the Scopus search engine shows that the number of scientific publications on the subject has seen an increasing order of magnitude (around 10 times), between 2011 and 2020, as shown in Fig. 1. The Scopus search engine is the largest abstract and citation database of peer-reviewed literature. The queries used in the search engine are: “Energy AND Communities”, “Local AND Energy System”, “Community AND Energy System”. All the results obtained from Scopus' queries have been carefully reviewed and filtered to include the papers related to energy communities only, not just part of the wider energy domain.

An energy community is made up of a number of producers, who are defined to be consumers but also producers [5]. Recently, Gjorgievski *et al.* [23] have reviewed the state-of-art literature on social arrangements, technical designs and the impact of energy communities. They have identified various gaps in the literature, and one of the highlights closely related to our work is the need to design a more realistic pay-off distribution among the community members for stable coalition of the energy community. Similarly, Seyfang *et al.* [24] have conducted a detailed UK-wide survey on energy community projects, and concluded that energy communities are diverse and rapidly growing. Recently, the modeling of energy community has gained increased attention from a social perspective focused on niche areas of: socio-technical energy system [25], social

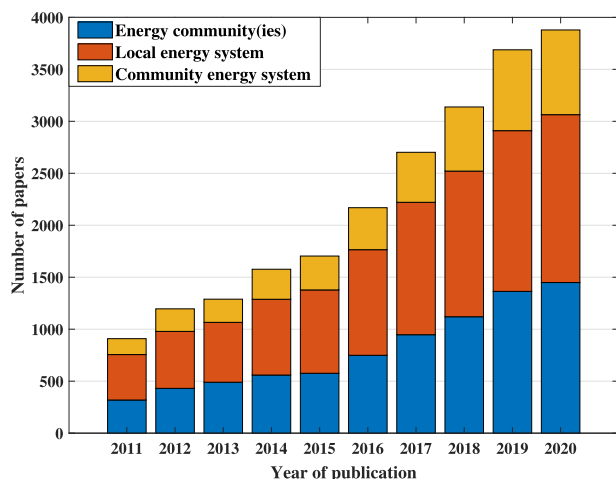


FIGURE 1. Evolution of scientific publications related to energy community.

innovations and dynamics [26], socio-technical energy transitions [27], social entrepreneurship [28], grassroots innovation [29], multi-sectoral approaches [30], social acceptance and participation [31], social investments [32] and social factors in AI research [33]. Huang *et al.* [34] have reviewed various simulation tools and models available for community energy system planning, design and optimization. Similarly, Mendes *et al.* [35] have surveyed numerous energy optimization and simulation tools for integrated community energy systems planning and analysis. Using a smart energy and AI perspective, other works have modeled a number of related concepts, such as Virtual Power Plant (VPP) optimisation [36]–[38], demand-side response aggregation [39]–[45], renewable energy curtailment in remote communities [46], [47], battery storage monitoring and optimisation [48]–[51], and P2P energy trading and blockchains [52]–[55].

Battery energy storage systems, along with renewable generators (solar PV, wind turbine) are the most common assets considered in the existing energy community models. In energy communities, individual households can invest in their own energy assets (renewable generation capacity and storage), or can jointly invest in the big community-owned energy assets and can then share energy and associated financial benefits within the community. Hence, techno-economic assessment between energy communities with individually-owned prosumer assets and models with community-owned assets have recently gained increased attention in the literature [7], [14]–[17]. Most of the studies focus on comparing the battery storage adoption at the individual household scale with storage adoption at the community scale. For instance, Dong *et al.* [14] have compared community energy storage (CES) to household energy storage (HES). Their results indicate that both HES and CES can improve the community self-consumption rate (SCR) and self-sufficiency rate (SRR). HES is found more suitable for households with lower demand profiles, while households with higher demand profiles benefit more from CES. The same authors' extended their study by comparing the

performance of HES and CES with demand side management (DSM) under ToU pricing scheme [7]. CES is found to be more effective at improving self-consumption for consumers and shaving peak demand for network operators. Similarly, Stelt *et al.* [15] have evaluated the techno-economic analysis of HES and CES for residential prosumers. The economic value of both HES and CES was assessed by considering the cost of energy imported from the grid. The results showed that both HES and CES can reduce the annual energy costs by 22 to 30%, and improve the use of on site PV generation by 23 to 29% compared to a baseline households without storage system. The economic feasibility of both HES and CES is found to be largely determined by the investment cost of the storage capacity per kWh. Similar comparison of storage adoption at the individual household level to storage adoption at the community level is studied by Barbour *et al.* [16]. Their results show that the community battery is better in terms of economic revenues compared to individual household batteries, as it requires less storage capacity overall and increases the self-consumption rate. Likewise, Walker & Kwon [17] have compared the economic and operational performance of individual and community shared storage. Their results also showed that the shared CES can achieve the maximum cost savings and significantly improve the utilization of energy storage.

Recently, Koirala *et al.* [56] have provided an overview of the state of the art in CES. Similarly, an overview of the economic potential and current research on CES was outlined by Sardi & Mithulananthan [57] and Strickland *et al.* [58]. The review states that CES have a huge potential to reduce import from the utility grid and thus maximize the self-consumption of the community. Hence, the advantages of CES over HES is well identified in the literature [7], [14]–[17], [59]–[64]. However, to our knowledge, most of the existing studies on comparison of individually-owned assets versus centrally located community-owned assets, while considering both the renewable generation and battery, have not included the battery degradation cost in their techno-economic analysis. Furthermore, although community assets are found to provide more benefits compared to individually-owned assets, still, the question of how to allocate financial gains from shared community-owned assets to the members of the community is not addressed in most of the existing frameworks.

Finally, several approaches have been proposed recently to integrate the network constraints such as electric cables thermal limits and voltage excursions in the market structures and trading strategies of the energy communities [6], [65]–[71]. However, most of the existing studies on the techno-economic analysis of individually-owned versus community-owned assets (including the authors' own prior work [21]) have not considered the network constraints. The assets might be prevented from exporting/consuming to/from the grid due to network constraints, thereby reducing the associated benefits. To our knowledge, the model in this paper is the first that considers such curtailment events in the energy community setting by including the power flow (grid constraints) in

the techno-economic analysis of individually-owned assets versus community-owned assets.

B. SHARING OF ENERGY, COST, AND FINANCIAL GAIN IN ENERGY COMMUNITIES

In the context of energy communities characterized with renewable energy systems, coalitional game theory has been identified as a promising solution for energy sharing schemes [72], cost allocation [73], and benefit redistribution [21] schemes among the community members. For instance, Alam *et al.* [19] proposed an energy exchange mechanism in rural communities that aimed to reduce battery usage and where approximated Shapley value was used for the distribution of benefits among the households. Although, they have proposed that the approximated Shapley value improves the computational time as compared to original Shapley value, but it still possess a significant computational challenge with the increase in the number of agents in the coalition. Recently, Moncecchi *et al.* [74] have proposed a two-level benefit distribution scheme based on coalitional game theory. At the first level, the benefit is distributed to a group of community members. Then, at the second level, the benefit is distributed proportionally to individual members. While various operational scenarios were studied, only few players (nine community groups only) were considered in the coalition formation. Similarly, Li [75] have proposed a cost-sharing scheme developed according to the Shapley value method. However, only four players are considered, thereby raising the issue of computational tractability and hence the practical application of the proposed redistribution mechanism is limited. Likewise, Chakraborty *et al.* [76] investigated the sharing of storage systems among consumers in a ToU pricing scheme using cooperative game theory. Sharing mechanism is illustrated using only five households which raises the issue of scalability and practicality as the household number increases in the coalition. Moreover, storage is considered ideal thereby neglecting the degradation aspect of the battery. In the work of Marzband *et al.* [77], cooperation among energy communities was studied in order to reduce the annual electricity cost, and profit redistribution mechanisms based on various solution concepts from cooperative game theory such as, Shapley, Nucleolus, and Merge and Split are proposed. Various energy, cost, and profit redistribution schemes based on coalitional game theory can also be found in [78]–[82]. However, one of the major challenges in redistribution schemes based on coalition game theory is the issue of scalability. Specifically, when determining the solution concepts such as Shapley values in a coalition, the computation becomes highly complex and time-consuming as the number of players increases in the coalition. Moreover, most of the existing redistribution frameworks are developed without considering network constraints, in which case the computation becomes more challenging. Thus, there is still a need to develop a redistribution mechanism that is fair, but also provide tractable computational performance that scales well with the increasing

number of members in the energy community coalition, while considering operational network constraints.

To address these limitations, we propose a study that first confirms the techno-economic benefits of community-owned assets versus individually-owned energy assets considering the network/grid constraints. Then, the novel fair redistribution mechanism introduced in our earlier work [21] is extended to include network operational constraints while being computationally tractable, and hence more practically applicable. In order to assess the benefits from installing various assets while including a comprehensive model of battery degradation, we propose an approach based on real time-series data of a community, and compare the benefits provided by community-owned assets with the benefits expected from individual assets, considering operational network constraints. In the next section, we present the energy community modeling approach.

III. METHODS

A. ENERGY COMMUNITY MODEL

In this work, we first aim to compare two configurations of energy communities. One configuration will consider the community as 200 individual agents, each one of them with his own consumption and local production, but without financial nor energy interaction between them. In such configuration, agents import electricity from the grid when their assets cannot cover their own consumption, whereas they can export electricity to the grid when they have production surplus. The second configuration corresponds to the case of an energy community in which agents invest together in community-owned assets, such as wind or solar production, and community batteries. The demand of agents is considered inflexible. A renewable generator (either wind turbine or a solar PV installation), a battery energy storage system and the utility grid are the three power sources considered for satisfying the inflexible demand at all times. A power flow diagram of an agent or of the energy community considered as a whole is shown in Fig. 2.

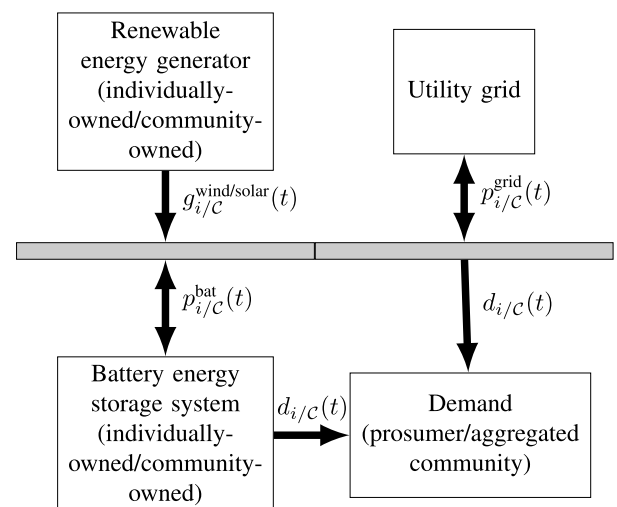


FIGURE 2. Power flow diagram of the energy community model.

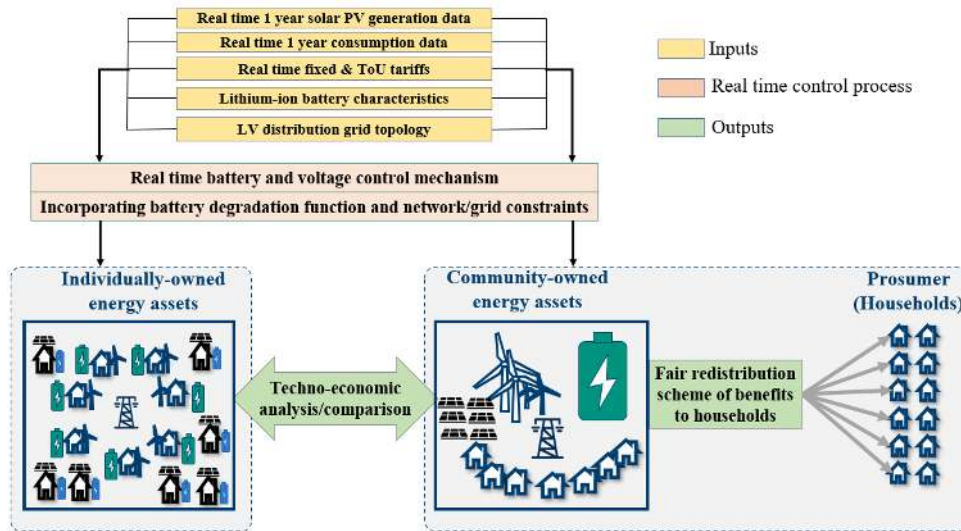


FIGURE 3. Overview of the energy community modeling approach.

We consider an energy community, composed of a group of individual prosumers (agents) connected to a low-voltage distribution network. To model a group of 200 individual prosumers, we consider that each individual has a consumption and a production from solar PV rooftop panel. Consumption data are half hourly demand profiles extracted from the dataset provided by the Thames Valley Vision End Point Monitor [83] project. We define, the community \mathcal{C} as the set of all agents i , and is defined as $\mathcal{C} = \{A_i \mid i \in [1, N]\}$ where $N = 200$ agents in our case.

The overall power balance at any given time t of an agent i or of the energy community \mathcal{C} is given by:

$$p_{i/\mathcal{C}}^{\text{grid}}(t) = d_{i/\mathcal{C}}(t) - p_{i/\mathcal{C}}^{\text{bat}}(t) - g_{i/\mathcal{C}}^{\text{wind/solar}}(t) \quad (1)$$

where $g_{i/\mathcal{C}}^{\text{wind/solar}}(t)$ is the power generated by the renewable generator, that can be individually owned, or owned by the community. $p_{i/\mathcal{C}}^{\text{grid}}(t)$ represents the power that an agent or that the community can buy/sell from/to the grid. $p_{i/\mathcal{C}}^{\text{bat}}(t)$ represents the power of the storage system (individually-owned, or centrally located and owned by the community), which is considered negative when the battery is charging (battery considered as a load), and positive when the battery is discharging (battery considered as a generator). $d_{i/\mathcal{C}}(t)$ is the power consumed by an agent or by the community considered as a whole, i.e the aggregated demand power of 200 agents.

However, the power flow diagram proposed in Fig. 2 does not include physical constraints such as electric cables thermal limits and voltage excursions. Therefore, in energy communities with important renewable production, such as the Orkney Islands considered in the ReFLEX project [22], agents may be prohibited from exporting power at particular times, due to electric cables overheat. As a result, grid constraints must also be added to the model described above.

This proposed energy community modeling approach is summarized in Fig. 3. We start first by modeling the power flows in an LV network describing the energy community in the following section.

B. LV NETWORK MODEL

To include physical constraints such as network constraints, we have considered a 13-bus radial distribution system to connect all agents of the community. This network model is adapted from the IEEE 13-bus network [84]. We first aim to compare two configurations of energy communities. First, a configuration with individually-owned distributed generation assets, such as solar PV and residential batteries. Households are randomly aggregated among the 13-buses, as presented in Fig. 4. Then, a second configuration in which distributed generation assets are owned by the community, and installed in a single location. Fig. 5 shows the location of assets and households in the configuration of centrally located, community-owned generation and storage assets.

Community-owned assets are connected to a unique bus without load, that was chosen to be in a central location of the grid, in order to reduce the risk of constraining the grid. Bus 1 represents the main connection to the transmission grid, and its voltage is set to reference voltage of 1 p.u with the base voltage of 236 V.

Power flow in this 13 bus grid model is computed for every time interval considered in our simulations in order to determine the voltages and power (active and reactive) flowing at every bus. The power flow computation follows a power approach in which the apparent power balance is stated for every bus of the grid. We define, $S_n = P_n + jQ_n$ the apparent power that is consumed or produced at bus n . $Z_{nk} = R_{nk} + jX_{nk}$ is the impedance of the line between bus n and bus k and $S_{nk} = P_{nk} + jQ_{nk}$ is the apparent power flowing between bus n and bus k . The power balance equations are

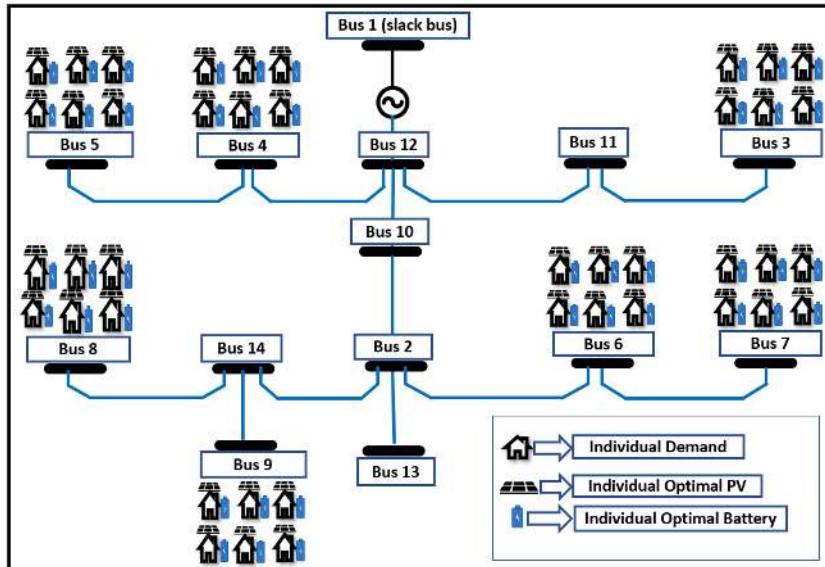


FIGURE 4. Electric network used in simulations with grid constraints for individually-owned assets.

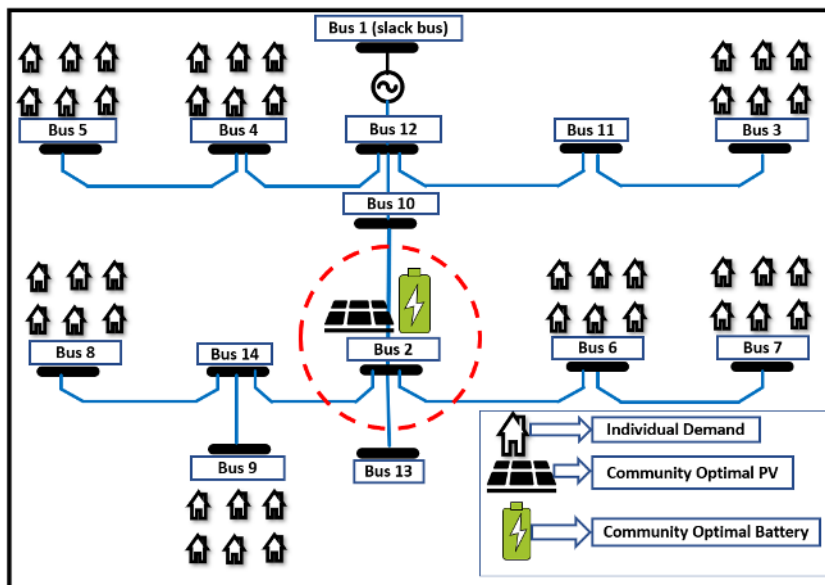


FIGURE 5. Electric network used in simulations with grid constraints for centrally located community-owned assets.

summarized in Eq. 2.

$$\begin{aligned}
 P_n &= |V_n| \sum_k |V_k| |Y_{nk}| \cos(\delta_k - \delta_n + \gamma_{nk}) \\
 Q_n &= |V_n| \sum_k |V_k| |Y_{nk}| \sin(\delta_k - \delta_n + \gamma_{nk}) \quad (2)
 \end{aligned}$$

where $\overline{Y_{nk}} = Y_{nk} e^{j\gamma_{nk}}$ is the admittance of the line connection between bus n and bus k . P_n is the total active power produced and consumed at bus n , which is considered positive if produced and negative if the power is consumed. Similarly, Q_n is the total reactive power produced (positive) and consumed (negative) at bus n . The voltage at bus n is defined

by $\overline{V_n} = V_n e^{j\delta_n}$, with δ_n the voltage angle. The power balance expressed in Eq. (2) is solved using the Newton-Raphson method, and gives the following two fundamental outputs:

- i The voltage at each bus, in amplitude and phase.
- ii The power (active and reactive) flowing through each bus.

Furthermore, in order to provide a techno-economic study that enables the comparison between the two configurations proposed (individually-owned and community-owned assets), we considered one year of data for load consumption [83] and solar PV production [85] with half-hourly time intervals, using Thames Valley Vision data. Power flows were

computed for the whole year. Also, we have linearly increased the power consumption of each household in order to consider an energy community in which voltage profiles are already close but still within the UK's upper and lower admissible voltage limits of 1.1 per unit (p.u) and 0.94 p.u. respectively for the whole year. Therefore, this setting consists in a case of normal operation with acceptable voltage and congestion profiles, while allowing us to study the potential impacts of installing various assets on the grid.

Indeed, the addition of solar PV or batteries in the LV grid changes power flows, and might create congestions or voltage excursions (i.e temporary fluctuations of voltage outside safe accepted limits). In such cases, the grid operator might consider the need for an ANM, that allows him to remotely control the injection of distributed generation assets. Therefore, due to this congestion/voltage excursion, assets might be prevented from exporting/consuming to/from the grid, reducing the benefits from their owners. For instance, when the grid is constrained with voltage excursions, then the exports from PV and exports/imports from/to battery are curtailed. This is why such curtailment events need to be accounted for in the energy community setting by including power flow (grid constraints) in the techno-economic analysis of individually-owned assets versus community-owned assets. The control algorithm of distributed generation assets, including the remote control from the Distribution System Operator (DSO) to prevent voltage out-of-bounds excursions, is defined in the following section.

C. BATTERY CONTROL ALGORITHM WITH VOLTAGE CONTROL MECHANISM

A battery control scheme consists of operational real-time decisions to charge or discharge the battery, based on the difference between the agent/community power consumption and its PV production. When the PV production exceeds the power consumed, the control scheme charges the battery if the bus voltage (V^{bus}) is within the permissible limits ($0.94 p.u \leq V^{\text{bus}} \leq 1.1 p.u$), until it reaches the full capacity. Any excess is exported and sold to the main grid, provided the V^{bus} is within the permissible limits. Whenever, the demand exceeds the PV production, the battery is discharged until it reaches its maximum allowable depth of discharge (DoD), provided the V^{bus} is within the permissible limits. Any remaining deficit is purchased and imported from the grid. The bus voltage is regulated within the safe permissible limits by controlling the export from the PV generator, and export/import from/to the battery assets.

The operation of the battery is constrained by the state of charge (SoC) levels, and a maximum power ($p^{\text{bat,max}}$) that the battery can be charged or discharged at, which corresponds to its maximum C-rating. In this work, Coulomb-counting method is used to estimate the SoC of the battery. The accuracy of this method depends mainly on how the current drawn from or to the battery is measured and on the nominal battery capacity [86]. In our study, the nominal battery capacity is updated at regular intervals of the simulation. This approach

is similar to the solutions implemented in commercial batteries.¹

At any given time t of a charging phase, the battery is charged with an efficiency (η^c) until it reaches the maximum battery capacity (SoC^{max}). Charging constraints are defined as:

$$SoC(t) \leq SoC^{\text{max}} \quad (3)$$

$$p^{\text{bat}}(t) \leq p^{\text{bat,max}} \quad (4)$$

Similarly, the battery can be discharged with an efficiency (η^d) until it reaches its minimum battery capacity (SoC^{min}). Discharging constraints are defined as:

$$SoC(t) \geq SoC^{\text{min}} \quad (5)$$

$$p^{\text{bat}}(t) \leq p^{\text{bat,max}} \quad (6)$$

The minimum battery capacity corresponds to the maximum allowable DoD.

In this section, we propose a *heuristic-based battery control* algorithm that aims to charge the battery when there is excess of power, and discharge the battery when there is a deficit of power, while maintaining the bus voltage (V^{bus}) within the permissible limits. The algorithm can be described as follows:

If $g^{\text{PV}}(t) > d(t)$, there is *excess of power* generated from the PV generator. The control strategy of the battery dictates the following:

- I Excess power is stored in the battery (charging operation), provided the $V^{\text{bus}}(t)$ due to bus power $P^{\text{bus}}(t)$ is within the permissible limits. $P^{\text{bus}}(t)$ is the total net active and reactive power of the bus at time t given by Eq. (2).
- II If the battery is full or if available power is greater than the maximum acceptable charging power, the agent/community sells the excess power to the utility grid at a selling price equal to $\tau^s(t)$, provided the $V^{\text{bus}}(t)$ due to bus power $P^{\text{bus}}(t)$ is within the permissible limits.

The resulting SoC profile, power at bus $P^{\text{bus}}(t)$, and the energy exported $e^s(t)$ to the grid during the identified duration of excess generation are determined as:

$$p^{\text{bat}}(t) = \frac{\min(\min([g^{\text{PV}}(t) - d(t)], p^{\text{bat,max}}), [SoC^{\text{max}} - SoC(t-1)])}{\eta^c \Delta t} \iff 0.94p.u \leq V^{\text{bus}}(t) \leq 1.1p.u \quad (7)$$

$$SoC(t) = SoC(t-1) + \eta^c p^{\text{bat}}(t) \Delta t \quad (8)$$

$$P^{\text{bus}}(t) = g^{\text{PV}}(t) - p^{\text{bat}}(t) \quad (9)$$

$$e^s(t) = [P^{\text{bus}}(t) - d(t)] \Delta t \iff 0.94p.u \leq V^{\text{bus}}(t) \leq 1.1p.u \quad (10)$$

where Δt corresponds to the duration of the considered time step.

¹ A number of commercial battery manufacturers such as ABB [87] propose an updated Coulomb-counting method for SoC estimation.

III If the excess PV power available for charging the battery or for export to grid violates the safe voltage limit, then the power export from the PV, and power import to battery are curtailed ($P^{curtailed}$) until the voltage is within the permissible limits, accordingly the $P^{bus}(t)$ is updated. When the generation from the PV is curtailed due to voltage violations, the demand is satisfied by importing energy ($e^b(t)$) from the utility grid at a buying price equal to $\tau^b(t)$. Whenever the $V^{bus}(t) > 1.1 p.u.$, the voltage is controlled as follows.

- i If the battery is fully charged, then the export from PV is curtailed and the bus power is updated as:

$$P^{bus}(t) = P^{bus}(t) - P^{curtailed} \quad (11)$$

If the updated $P^{bus}(t) > 0$, then the excess energy is exported to the utility grid:

$$e^s(t) = [P^{bus}(t) - d(t)] \Delta t \quad (12)$$

If the updated $P^{bus}(t) < 0$, then the deficit energy is imported from the utility grid:

$$e^b(t) = [d(t) - P^{bus}(t)] \Delta t \quad (13)$$

- ii If the battery is in the process of charging, then the power export from PV and power import to battery are curtailed, and the bus power is updated as:

$$P^{bat}(t) = \min(\min([P^{bat}(t) + P^{curtailed}], P^{bat,max}), \frac{[SoC^{max} - SoC(t - 1)]}{\eta^c \Delta t}) \quad (14)$$

$$P^{bus}(t) = g^{PV}(t) - P^{bat}(t) \quad (15)$$

If the updated $P^{bus}(t) > 0$, then the excess energy is exported to the utility grid:

$$e^s(t) = [P^{bus}(t) - d(t)] \Delta t \quad (16)$$

If the updated $P^{bus}(t) < 0$, then the deficit energy is imported from the utility grid:

$$e^b(t) = [d(t) - P^{bus}(t)] \Delta t \quad (17)$$

Similarly, if $g^{PV}(t) < d(t)$, then there is a deficit in power supplied by the PV generator. During this time, the demand is satisfied by discharging the battery, provided the battery capacity is above the minimum SoC and the bus voltage (V^{bus}) is within the permissible limits. Otherwise, the deficit power is imported from the utility grid. A flowchart of the proposed control strategy is shown in Fig. 6. Algorithm 1 outlines this heuristic if-then rule based control strategy.

Most of the time the voltage excursion is characterized predominantly by over-voltage phenomenon (i.e high voltage violations $V^{bus}(t) > 1.1 p.u.$). Hence, the voltage control mechanism for the case with $V^{bus}(t) > 1.1 p.u$ is only included in the control scheme. However, if the bus voltage

violates the lower permissible limit ($V^{bus}(t) < 0.94 p.u$) and $g^{PV}(t) > d(t)$, then the bus voltage can be controlled by limiting the battery charging until it is within the permissible limit. If $g^{PV}(t) < d(t)$, then the bus voltage can be controlled by increasing the reactive power production from the battery.

Whenever the bus voltage (V^{bus}) violates the permissible limits, then the grid is constrained, hence the exports from PV and exports/imports from/to battery are curtailed. This reduces the financial benefits offered by the assets. The economic parameters to assess and compare the benefits of community-owned assets with individually-owned assets is presented in the next section.

D. ASSESSMENT OF ENERGY COMMUNITY EFFICIENCY

The main aim of the economic study of the energy community is to determine the benefits provided by assets (renewable generation capacity and storage) to prosumers, subjected to network and operational constraints. To achieve this, the presented algorithm 1 is implemented by considering the different pricing schemes. A yearly energy bill savings, which is a fairly intuitive indicator, is used to compare the economic performance of investments in individually-owned assets and community-owned assets. In this section, we provide the key economic performance indicator adopted in the proposed comparative study.

1) PRICING SCHEMES OF THE COMMUNITY

In this study, we did not consider the feed in tariff, and considered two types of pricing schemes for energy imports from the main utility grid. Export tariff to the grid was not included as many developed countries worldwide (such as the UK or the EU), guaranteed feed-in-tariffs (FITs) for renewable electricity generated by small DERs are being phased out as a support mechanism, i.e. they are gradually reduced or are well below retail tariffs available from large operators [15]. For instance, in the UK, FITs are no longer available to producers of any size since 31st March 2019 [88]. A fixed and a dynamic ToU import tariffs were considered as described below:

- **Fixed tariff:** a fixed tariff of 16 pence/kWh was adopted after comparing the fixed electricity prices offered by various UK-based electricity suppliers using web-tools in price comparison site Money Supermarket [89]. This website is one of the several price comparison sites approved and accredited by the Office of Gas and Electricity Markets (Ofgem) [90], the government regulator for the electricity and downstream natural gas markets in UK.
- **Dynamic tariff (ToU):** the dynamic ToU tariff was based on Agile Octopus [91] offered by Octopus Energy, a UK-based electricity supplier. Agile Octopus tariff consist of a maximum price of 35 pence/kWh, an average price of 15.9 pence/kWh, and a minimum of 2.8 pence/kWh. Both the fixed and dynamic ToU

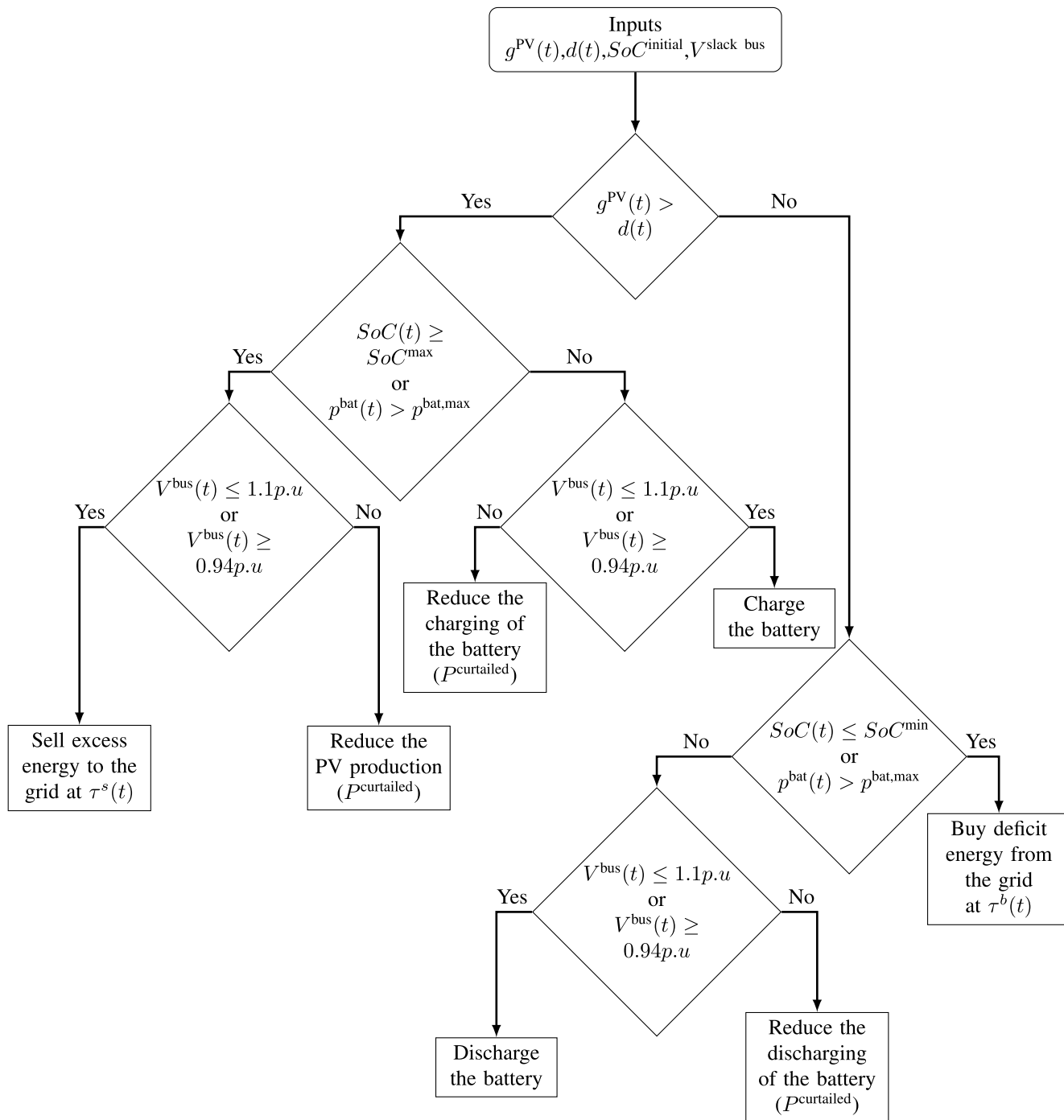


FIGURE 6. Flowchart of battery and voltage control scheme.

pricing schemes corresponds to real tariffs applied in 2020.

2) TECHNO-ECONOMIC INDICATORS

The economic value of both community-owned assets and individually-owned assets can be assessed and compared by considering the reduction of the sum of the annual electricity bill of all the households from the energy community. The yearly bill $b(T)$ of an agent/community can be expressed as the sum of the cost of the annual energy consumption and the depreciation cost of the assets c^A , minus

the sum of revenues earned by exports to the grid, as shown below:

$$b(T) = \sum_1^T e^b(t)\tau^b(t) - \sum_1^T e^s(t)\tau^s(t) + c^A(T) \quad (18)$$

where the energy import $e^b(t)$ at time step t is given by Eq. (19), with P^{house} the power imported (if positive) or exported (if negative) by the considered household.

$$e^b(t) = [d(t) - P^{house}(t)] \Delta t \quad (19)$$

Algorithm 1: Battery and Voltage Control Algorithm

```

1 Input:  $g^{PV}(t), d(t), \tau^b(t), \tau^s(t), \eta^c, \eta^d, SoC^{initial}, SoC^{max}, SoC^{min}, p^{bat,max}$ 
2 Set:  $V^{slack\ bus} = 1 p.u$ 
3 for  $t = 1 : T$  do
4    $\forall t \in [0, T]$ , excess of energy or deficit in energy is determined
5   if  $g^{PV}(t) \geq d(t)$  then
6      $p^{bat}(t) = \min \left( \min ([g^{PV}(t) - d(t)], p^{bat,max}), \frac{[SoC^{max} - SoC(t-1)]}{\eta^c \Delta t} \right) \Leftarrow 0.94 p.u \leq V^{bus}(t) \leq 1.1 p.u$ 
7      $SoC(t) = SoC(t-1) + \eta^c p^{bat}(t) \Delta t$ 
8      $p^{bus}(t) = g^{PV}(t) - p^{bat}(t)$ 
9      $e^s(t) = [p^{bus}(t) - d(t)] \Delta t \Leftarrow 0.94 p.u \leq V^{bus}(t) \leq 1.1 p.u$ 
10    while  $V^{bus}(t) > 1.1 p.u$  do
11      if  $p^{bat}(t) \geq p^{bat,max} \parallel SoC(t) \geq SoC^{max}$  then
12         $p^{bus}(t) = p^{bus}(t) - p^{curtailed}$ 
13        if  $p^{bus}(t) > 0$  then
14           $e^s(t) = [p^{bus}(t) - d(t)] \Delta t$ 
15        else
16           $e^b(t) = [d(t) - p^{bus}(t)] \Delta t$ 
17        end
18      else
19         $p^{bat}(t) = \min \left( \min ([p^{bat}(t) + p^{curtailed}], p^{bat,max}), \frac{[SoC^{max} - SoC(t-1)]}{\eta^c \Delta t} \right)$ 
20         $p^{bus}(t) = g^{PV}(t) - p^{bat}(t)$ 
21        if  $p^{bus}(t) > 0$  then
22           $e^s(t) = [p^{bus}(t) - d(t)] \Delta t$ 
23        else
24           $e^b(t) = [d(t) - p^{bus}(t)] \Delta t$ 
25        end
26      end
27    end
28  else
29     $p^{bat}(t) = \min (\min ([d(t) - g^{PV}(t)], p^{bat,max}), \eta^d [SoC(t-1) - SoC^{min}]) \Leftarrow 0.94 p.u \leq V^{bus}(t) \leq 1.1 p.u$ 
30     $SoC(t) = SoC(t-1) - \frac{p^{bat}(t)}{\eta^d} \cdot \Delta t$ 
31     $p^{bus}(t) = g^{PV}(t) + p^{bat}(t)$ 
32     $e^b(t) = [d(t) - p^{bus}(t)] \Delta t$ 
33    while  $V^{bus}(t) > 1.1 p.u$  do
34      if  $p^{bat}(t) \leq 0 \parallel SoC(t) \leq SoC^{min}$  then
35         $p^{bus}(t) = \max (0, p^{bus}(t) - p^{curtailed})$ 
36         $e^b(t) = [d(t) - p^{bus}(t)] \Delta t$ 
37      else
38         $p^{bat}(t) = \min (\max (0, [p^{bat}(t) - p^{curtailed}]), \eta^d [SoC(t-1) - SoC^{min}])$ 
39         $p^{bus}(t) = g^{PV}(t) + p^{bat}(t)$ 
40         $e^b(t) = [d(t) - p^{bus}(t)] \Delta t$ 
41      end
42    end
43  end
44 end
45 Output:  $\forall t \in [0, T]$ ,  $SoC(t)$ , input to rainflow cycle counting algorithm used to calculate the battery depreciation factor,  $e^s(t)$  energy exported to utility grid,  $e^b(t)$  energy imported from grid,  $p^{bus}(t)$  bus power, and  $V^{bus}(t)$  bus voltage profile.

```

Similarly, the energy export $e^s(t)$ at time step t is given by Eq. (20).

$$e^s(t) = [p^{bus}(t) - d(t)] \Delta t \quad (20)$$

However, as many countries have reduced or removed export prices under the form of feed-in tariffs, our analysis will not include revenues from energy export. Thus, the yearly bill without feed-in tariff is determined

as:

$$b(T) = \sum_1^T e^b(t)\tau^b(t) + c^A(T) \quad (21)$$

c^A represents the depreciation cost which is due to the usage of the asset within the considered period. For example, for a considered period T equal to one year in which the asset is used following the manufacturer's recommendations, $c^A(T)$ corresponds to the annualized cost of the asset, given as follows:

$$c^A(T) = \frac{\text{Asset cost}}{\text{Life time (in years)}} \quad (22)$$

In the techno-economic analysis, the battery depreciation cost can be greater or equal to the depreciation cost mentioned in batteries manufacturer specifications, the depreciation can be greater if the useful lifetime is small. A battery useful lifetime depends on the frequency and depth of charge/discharge cycles during the battery's operation. Frequent charging and discharging operations lead to cyclic ageing and incurs an extra cost as it accelerates the depreciation of the battery and reduces its useful lifetime. This translates into an impact on the total cost of operation and maintenance of the battery, especially as energy storage is one of the most expensive component of hybrid energy systems composed of renewable generation and storage assets. In the cyclic operation of the battery, a cycle is defined to have been completed when the battery depth of discharge (DoD) has returned to the starting point of the cycle. Furthermore, *regular and irregular cycles* can also be distinguished depending on the starting and ending SoC of the cycle, as defined below:

- *Regular cycles*: in this cycling process the starting SoC is 100%, then it is discharged to a certain SoC corresponding to a specific DoD and recharged back to 100% SoC. For example, 100% SoC-to-60% SoC-back to 100% SoC corresponds to 40% DoD cycle.
- *Irregular cycles*: in this case, the starting SoC is other than 100% SoC, i.e. cycles start at any arbitrary SoC value. For example, 70% SoC-to-30% SoC-back to 70% SoC, which also corresponds to a 40% DoD discharge cycle, relative to the starting SoC.

In both cases, the DoD may be same, but the battery degradation is sensitive to the starting SoC. An important aspect to be noted here is that the number of cycles versus DoD specified in manufacturer data-sheets are based on regular cycles only. But, in real-life applications, the battery can hardly run on regular cycles from 100% SoC to a specific DoD. Hence, an important characteristics when integrating battery storage degradation in the economic analysis, is to assess the impacts of irregular cycles.

In this paper, a detailed Lithium-ion *battery degradation model* developed in our previous work [21] is used to determine the battery depreciation factor (DF) to estimate the battery useful lifetime. In the model, the useful life of the

battery is estimated by considering the cyclic degradation due to both regular and irregular cycles. The rainflow cycle counting algorithm is used to count regular and irregular cycles by considering the SoC profile generated from the battery control algorithm 1. The depreciation factor (DF) is expressed as follows:

$$DF = DF^{\text{regular}} + DF^{\text{irregular}} \quad (23)$$

where DF^{regular} and $DF^{\text{irregular}}$ correspond to the depreciation factor for regular and irregular cycles respectively. When the DF value is equal to 1, this means the battery has reached its end of life (EoL), hence the battery needs to be replaced. EoL is normally defined as a state of the battery when the maximum capacity of the battery reduces to 80% of its rated initial capacity.

Taking into consideration the depreciation resulting from the battery operation, the computation of the depreciation cost c^A in Eq. (18), & (21) is updated as follows:

$$c^A(T) = \max\left(\frac{1}{DF}, \frac{\text{Asset cost}}{\text{Life time (in years)}}\right) \quad (24)$$

Finally, as outlined by Eq. (21), the annual bill for agent i and the community \mathcal{C} are defined as:

$$b_i(T) = \sum_1^T e_i^b(t)\tau^b(t) + c_i^A(T) \quad (25)$$

$$b_{\mathcal{C}}(T) = \sum_1^T e_{\mathcal{C}}^b(t)\tau^b(t) + c_{\mathcal{C}}^A(T) \quad (26)$$

where, $e_i^b(t)\tau^b(t)$ is the cost of energy imports from the utility grid by agent i at time t and $c_i^A(T)$ is the depreciation cost of the battery owned by agent i in the considered period T . Similarly, $e_{\mathcal{C}}^b(t)\tau^b(t)$ is the cost of energy imported from the utility grid by the community as a whole at time t and $c_{\mathcal{C}}^A(T)$ is the depreciation cost of community-owned battery for the considered period T .

E. MECHANISM DESIGN FOR FAIR REDISTRIBUTION OF BENEFITS FROM COMMUNITY-OWNED ASSETS TO INDIVIDUAL HOUSEHOLDS

In the case of community owned assets, the revenues generated by the community-owned distributed generation system (PV and battery) can be distributed to the members of the community. However, this raises the key research question of how to fairly redistribute the energy outputs (and hence the financial benefits) from the community-owned assets to the individual members of the community. In this section, we present the fair redistribution scheme to fairly redistribute the benefits from the community-owned assets. Also, in order to test the advantages of the proposed redistribution mechanism, we present in this section state-of-the-art redistribution method, used in current practice in such projects, that will be used for comparison.

1) MARGINAL COST REDISTRIBUTION METHOD

In this section, we present a redistribution method based on the marginal contribution of each agent, a key concept in cooperative game theory. The marginal contribution $\Theta_i(T)$ of an agent i for the period T represents the difference that an agent makes to the value of a given coalition in the community. Specifically, the marginal contribution $\Theta_i(T)$ is a metric that assess how much each agent i contributes to the reduction of the energy bill of the community as a whole.

Savings of the community after one year ($T = 1$ year), noted as $\Pi_C(T)$, are defined by the difference between the sum of all agents annual bills before the community assets were installed (which corresponds to the baseline scenario without assets), and $b_C(T)$ i.e. the energy bill for the whole community after one year with community-owned assets. Hence, the community savings over time period T correspond to the bill reduction for the whole community over that period, as shown below:

$$\Pi_C(T) = \sum_{i=1}^N b_i^0(T) - b_C(T) \quad (27)$$

where $b_i^0(T)$ is the baseline bill (bill without assets) for prosumer i before any asset was installed. In order to compute a fair redistribution of the community savings among the individual agents, the contribution $\Theta_i(T)$ of each agent to these community savings is computed. To compute the marginal contribution of an agent i , we remove agent i from the community of 200 agents (total community), and recompute the community savings of this virtual community of 199 agents (reduced community). The *marginal contribution* $\Theta_i(T)$ of agent i is defined as the difference between the total community savings $\Pi_C(T)$ and the savings of the reduced community $\Pi_{C \setminus \{i\}}(T)$, as shown below:

$$\Theta_i(T) = \Pi_C(T) - \Pi_{C \setminus \{i\}}(T) \quad \forall i \in C \quad (28)$$

where C is the community of 200 households. Once the marginal contribution $\Theta_i(T)$ is computed for all the agents, we distribute community savings $\Pi_C(T)$ among the individual agents based on the following equation:

$$\Gamma_i(T) = \Pi_C(T) \frac{\Theta_i(T)}{\sum_{i \in C} \Theta_i(T)} \quad \forall i \in C \quad (29)$$

where $\Gamma_i(T)$ is the amount of money redistributed to agent i after period T .

Hence, the new bill of agent i for the time period T , noted $b_i^*(T)$ can be computed as follows:

$$b_i^*(T) = b_i^0(T) - \Gamma_i(T) \quad \forall i \in C \quad (30)$$

2) MARGINAL COST REDISTRIBUTION METHOD WITH NETWORK CONSTRAINTS

The computation of the marginal cost redistribution method in a setup that considers network constraints is computationally expensive as it requires to recompute the marginal contribution of every agent, which requires power-flow

computation for every time step of the considered period (e.g. one year). Hence, for larger network, the redistribution mechanism by marginal cost redistribution method may not be computationally tractable.

To address this computational challenge while considering the network constraints, we propose an approximation method. First, we compute the agents i new bill $b_i^{*(-)}(T)$ for the case without network constraints using the Eq. (30) as expressed in Eq. (31):

$$b_i^{*(-)}(T) = b_i^0(T) - \Gamma_i(T) \quad \forall i \in C \quad (31)$$

Then, we compute the difference between community yearly bill *with network constraints* ($b_C^{NC}(T)$) and community yearly bill *without network constraint* ($b_C^-(T)$). Finally, the equal part of the computed difference in the bill is distributed equally among the agents by adding to the new bill $b_i^{*(-)}(T)$ obtained using Eq. (31). Finally, the new bill of agent i with network constraints ($b_i^{*(NC)}(T)$) is determined as expressed in Eq. (32).

$$b_i^{*(NC)}(T) = b_i^{*(-)}(T) + \frac{b_C^{diff}}{N} \quad (32)$$

where $N = 200$ agents (households) in our case. b_C^{diff} is the difference between community yearly bill considering network constraints and community yearly bill without network constraints as expressed in Eq. (33).

$$b_C^{diff} = b_C^{NC}(T) - b_C^-(T) \quad (33)$$

3) INSTANTANEOUS POWER REDISTRIBUTION METHOD WITH NETWORK CONSTRAINTS

To test the advantages of the proposed marginal cost redistribution method with network constraints, we compare its benefits with the state-of-the-art instantaneous power redistribution method [92]. In this method, an instantaneous PV power $g_C^{PV}(t)$ produced by community-owned PV generator is distributed among individual agents based on their instantaneous demand $d_i(t)$. In other words, the PV power allocated to agent i at each time step is determined as:

$$g_i^{PV}(t) = g_C^{PV}(t) \times \frac{d_i(t)}{\sum_{i \in C} d_i(t)} \quad (34)$$

Then, the new bill of each agent i is computed using Eq. (25).

IV. EXPERIMENTAL RESULTS

In this section, we present the results in two parts: first, we discuss the financial benefits obtained from community-owned assets and individually-owned assets considering the network constraints, and compare it with the case without network constraints. Then, we propose a comparison of various benefit redistribution schemes described in Section III-E.

TABLE 1. Sum of individual agents optimal solar PV capacities, and community optimal solar PV capacity for both the fixed tariff of 16 pence/kWh and dynamic Agile Octopus ToU tariff.

Assets	Fixed Tariff	ToU Tariff
	Optimal capacity (kW)	Optimal capacity (kW)
Sum of individual agents optimal solar PV's	258	297
Community optimal solar PV	309	347

TABLE 2. Sum of individual agents optimal battery capacities and community optimal battery capacity for both the fixed tariff of 16 pence/kWh and dynamic Agile Octopus ToU tariff.

Assets	Fixed Tariff	ToU Tariff
	Optimal capacity (kWh)	Optimal capacity (kWh)
Sum of individual agents optimal batteries	513	602
Community optimal battery	642	620

A. MODEL INPUT DATA

1) RENEWABLE GENERATION DATA

For the analysis we have used a real solar radiation data from the UK Met Office Integrated Data Archive System (MIDAS) [85] provided by British Atmospheric Data Centre (BADC). The MIDAS dataset consists of meteorological observations from weather stations located at various parts of the UK. The hourly solar radiation data obtained in kJ/m^2 was converted to W/m^2 , then it was normalized to generate solar PV power in Watts (W). Finally, one hour resolution data was converted to half hourly data using double spline interpolation function, to make it compatible with the resolution of the demand data.

2) UNITARY COST OF ASSETS

A battery cost of 150 £/kWh was assumed in this work based on 2020 Lithium-ion battery forecasts estimated by BloombergNEF [93], [94]. According to BloombergNEF [94] and PV Europe-Energy Storage [95], battery costs are expected to drop even further in the following years with an estimated cost of less than \$100/kWh expected in 2023. The chosen battery cost of 150 £/kWh for the year 2020 is consistent with the Lithium-ion battery cost forecasts for 2021 and 2025 published in the McKinsey quarterly report [96]. A cost of 1100 £/kW for solar PV generation capacity was assumed based on the production and installation cost of solar PV according to EIA, Annual Energy Outlook 2021 [97]. This cost reflects the average values of levelized cost of electricity (LCOE) and levelized avoided cost of electricity (LACE) for solar PV generating technologies entering service in 2025.

B. OPTIMAL SIZING OF ASSETS

First, it is necessary to determine the capacity of assets installed. In this study, we chose to use an optimal size for both individual assets and community assets. An optimal size of PV or battery corresponds to the size that provides the

minimal simple payback period. First, we have considered solar PV assets sizing without any storage. Then, we determined the optimal battery size for each agent and for the community. Therefore, for both assets types (PV and batteries), we considered investment cost and degradation due to their operation. Results of the optimal assets sizing are shown in Table 1 for PV, and Table 2 for battery. The computation of the simple payback period for each asset is based on simulations using the battery control algorithm 1 for one year.

The potential impacts of installing these various assets (with optimal capacities) on the grid, and the corresponding economic analysis is presented in the following section.

C. ECONOMIC COMPARISON OF INDIVIDUAL VERSUS COMMUNITY ASSETS

As a reminder, the 13-bus grid model for the 200 households community with optimal capacity assets (as shown in Table 1 & 2) is shown in Fig. 4 & 5 as described in Section III-B. Yearly bus voltages are computed every half-hour of the year by running power flow simulation over the network, with the given consumption and production profiles. Based on these voltage profiles, the impact of considering the grid on the profitability of DERs and battery energy storage system (BESS) is studied under various scenarios. The scenarios correspond to different assets installation schemes in the network. The yearly bills are computed under the various scenarios considering the network constraints, and then compared with the yearly bills computed without network constraints in order to assess how grid constraints can impact the deployment of individual and community owned assets. Yearly bills are computed for both the fixed tariff of 16 pence/kWh using [89] and dynamic ToU Agile Octopus [91] tariff pricing schemes under various scenarios as presented below:

1) SCENARIO 1: WITHOUT ANY LOCAL RENEWABLE GENERATION OR BATTERY ASSETS

In this scenario, we only consider the demand of households, without any assets. This setting defines a *baseline*

TABLE 3. Economic comparison of individually-owned and community-owned assets under baseline scenario 1 (without assets) for both the fixed tariff of 16 pence/kWh and dynamic Agile Octopus ToU tariff.

Without assets (baseline)	With network constraint		Without network constraint	
	Fixed Tariff	ToU Tariff	Fixed Tariff	ToU Tariff
	Annual bill (£)	Annual bill (£)	Annual bill (£)	Annual bill (£)
Sum of individual agents yearly bills	134455	143923	134455	143923
Community yearly bill	134455	143923	134455	143923

scenario, against which the other scenarios can be compared. The yearly bills with network constraints under this baseline scenario are computed for both the fixed and ToU tariffs, and compared with the yearly bills computed without network constraints. Table 3 shows the sum of individual agents annual bills and the community annual bill determined without any assets.

As described in Section III-B, in the baseline scenario without any assets, the grid is not constrained as there is no voltage excursion nor cable overloading. Hence, the sum of individual annual bills and community annual bill are equal for both cases with and without network constraints. Furthermore, it can be observed that without assets, the community annual bill is equal to the sum of individual annual bills, which is expected as the community represents the aggregated demand profiles of the individual households, and there are no local renewable generation or battery storage assets.

2) SCENARIO 2: WITH SOLAR PV RENEWABLE GENERATOR ASSET ONLY WITHOUT BATTERY

In this scenario, we consider the demand of households, with renewable generator asset only, without battery storage (in the experiments in this paper, the renewable generation is shared solar, but the model is general, hence this could also be a shared community wind turbine). The yearly bills with network constraints under this scenario are computed for both the fixed and ToU tariffs, and compared with the yearly bills computed without network constraints. Table 4 shows the sum of individual agents annual bills and community annual bill obtained under this scenario.

Fig. 7 shows the yearly voltage profiles of the buses obtained for the network with individually distributed optimal solar PV’s. We can see that there is a rise in voltage during the summer months due to high power production from solar PV, whereas voltages reduces during the winter months. However, the rise in the voltage is within the permissible limits. Hence, the exports from individual PV’s are not curtailed. Thus, the sum of individual yearly bills computed with network constraints and without network constraints are equal (as shown in Table 4).

Unlike the case of individual assets, Fig. 8 shows the yearly voltage profiles of the buses obtained for the network with centrally located community-owned, optimally-sized solar PV, if the grid was not curtailing any asset. We can see that if there is no control from the grid operator, the bus voltages

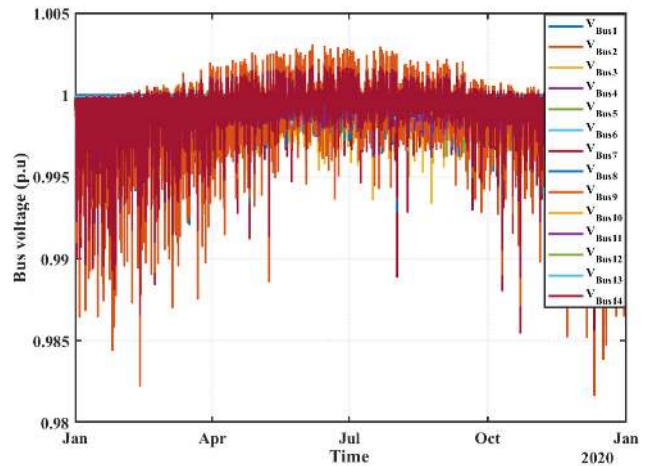


FIGURE 7. Yearly buses voltage profiles of the network with individually-owned optimal PV’s without battery.

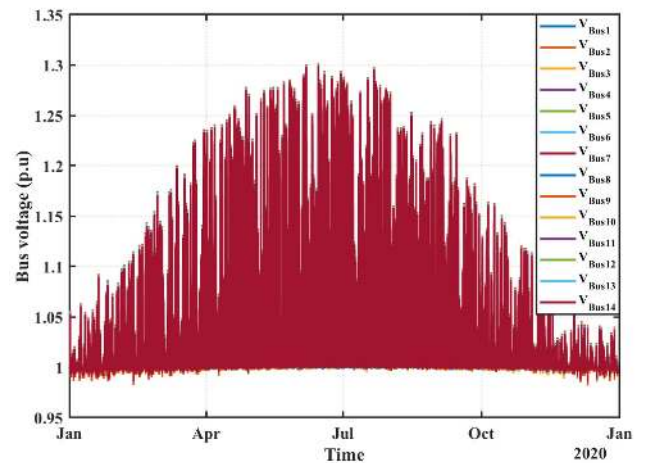


FIGURE 8. Yearly buses voltage profiles of the network with community-owned optimal PV only without voltage control mechanism.

rise above 1.1 p.u the highest permissible limit ($0.94 p.u \leq V^{bus} \leq 1.1 p.u$). In practice, the grid operator would not allow such voltage excursions, and may curtail assets exporting too much power. In this case, the grid will curtail the community-owned asset every-time the voltage rise above 1.1 p.u. Fig. 9 shows the voltage profile of the buses after implementing the voltage control mechanism by grid operator as described in Section III-C.

This curtailment reduces the financial benefits offered by the community-owned solar PV. It can be observed in Table 4

TABLE 4. Economic comparison of individually-owned and community-owned assets under scenario 2 (PV only without battery) for both the fixed tariff of 16 pence/kWh and dynamic Agile Octopus ToU tariff.

With only solar PV	With network constraint		Without network constraint	
	Fixed Tariff	ToU Tariff	Fixed Tariff	ToU Tariff
	Annual bill (£)	Annual bill (£)	Annual bill (£)	Annual bill (£)
Sum of individual agents yearly bills	122557	129589	122557	129589
Community yearly bill	119315	126371	117092	123154

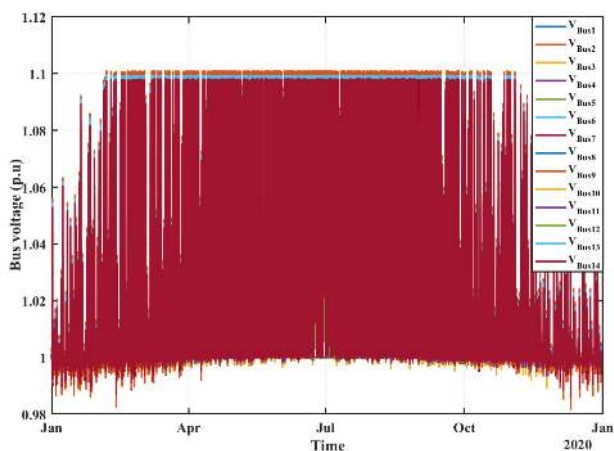


FIGURE 9. Yearly buses voltage profiles of the network with community-owned optimal PV only after implementing the voltage control mechanism.

that when the network constraints is considered the community annual bill increases by £2223 for flat tariff and by £3217 for ToU tariff compare to the case without network constraints. Thus, the overall saving of the energy community is reduced when grid operations are considered.

3) SCENARIO 3: WITH BOTH SOLAR PV RENEWABLE GENERATOR AND BATTERY STORAGE ASSETS

In this scenario, we consider the demand of households, with both renewable generator and the battery storage assets. The yearly bills with network constraints under this scenario are computed for both the fixed and ToU tariffs, and compared with the yearly bills computed without network constraints. Table 5 shows the sum of individual agents annual bills and community annual bill obtained under this scenario.

Fig. 10 shows the yearly voltage profiles of the buses obtained for the network with individually distributed optimal solar PV’s and optimal batteries. Similar to scenario 2, we can observe the rise in the bus voltages, and the seasonal effects in the voltage profiles. In this scenario also, the rise in the voltages are within the permissible limits. As the voltages are within the thresholds, the grid is not constrained, hence the exports from the individual PV’s and export/import from/to individual batteries are not curtailed. Thus, the sum of individual yearly bills computed with network constraints and without network constraints are equal as the grid is not

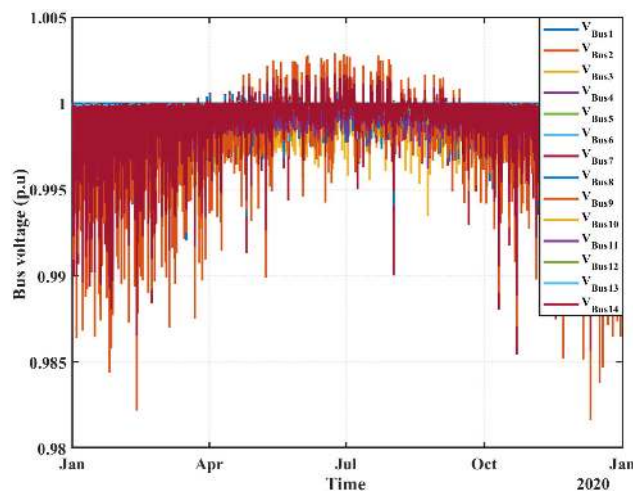


FIGURE 10. Yearly buses voltage profiles for the scenario with individually-owned optimal PV’s and optimal batteries.

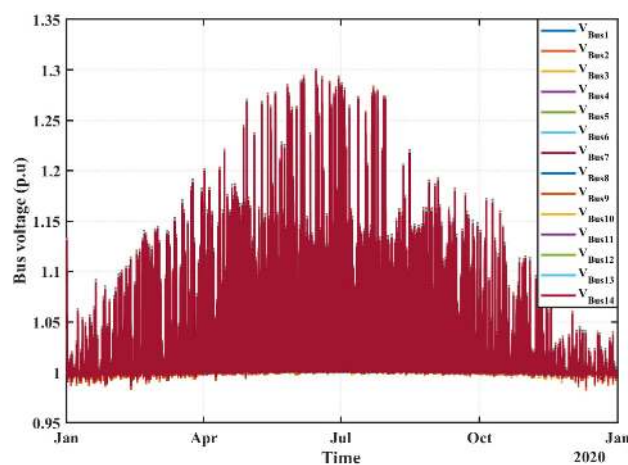


FIGURE 11. Yearly buses voltage profiles of the network with community-owned optimal PV and optimal battery assets without voltage control mechanism.

constrained when both the individual PV’s and batteries are installed (as shown in Table 5).

In the case with community-owned optimal PV and optimal battery, Fig. 11 shows the yearly voltage profiles of the buses obtained for the network without implementing the voltage control mechanism. Similar to the Scenario 2 with community PV only, the bus voltages rise above the 1.1 p.u the highest permissible limit. In such case,

TABLE 5. Economic comparison of individually-owned and community-owned assets under scenario 3 (both PV and battery) for both the fixed tariff of 16 pence/kWh and dynamic Agile Octopus ToU tariff.

With both solar PV and battery	With network constraint		Without network constraint	
	Fixed Tariff	ToU Tariff	Fixed Tariff	ToU Tariff
	Annual bill (£)	Annual bill (£)	Annual bill (£)	Annual bill (£)
Sum of individual agents yearly bills	118488	122419	118488	122419
Community yearly bill	115664	121326	113790	117307

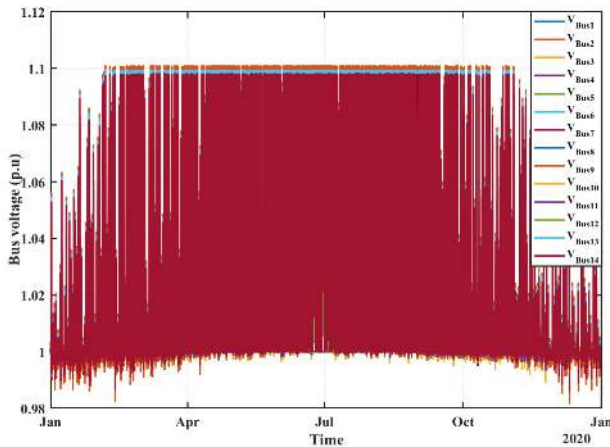


FIGURE 12. Yearly buses voltage profiles of the network with community-owned optimal PV and optimal battery after implementing the voltage control mechanism.

the grid operator will control the voltage by curtailing the export/import from/to community-owned assets as described in Section III-C. Fig. 12 shows the voltage profile of the buses after implementing the voltage control mechanism.

This curtailment reduces the overall saving of the community. This effect can be observed in Table 5, where the annual bill with network constraints is increased by £1874 for flat tariff and £4019 for ToU tariff as compared to yearly bill computed without network constraints.

Overall, for the community with individually-owned assets, the bus voltages remains within permissible limits. As the voltages are within the thresholds, export/import from/to the assets are not curtailed, and the bills in the scenarios with and without network constraints are identical.

Fig. 8 and 11 show that there are voltage excursions in the grid when the community-owned assets are installed. In such case, the grid operator may curtail assets exporting/importing too much power. Hence, the community-owned assets gets curtailed every-time the voltage rise above 1.1 p.u. It is important to note that the voltage at bus 2 the location of community-owned PV and battery is not controlled. As shown in the Fig. 5, the community-owned PV and battery are connected to bus 2 which makes the power export being concentrated at one location, thus with the community-owned assets the voltage rises more than in the scenario with individually-owned assets. Whenever the voltage rises above the permissible limit then the exports from

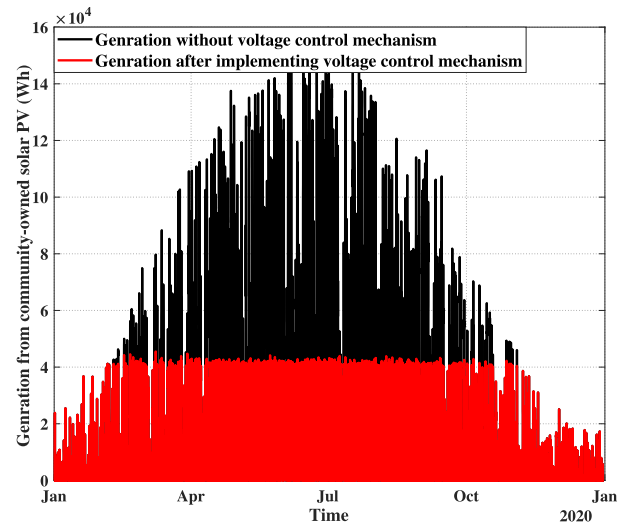


FIGURE 13. Yearly generation from community-owned solar PV with and without voltage control mechanism.

PV and exports/imports from/to battery are curtailed until the voltage is within the threshold. In order to illustrate this curtailment effect, the yearly generation from community-owned solar PV with and without voltage control mechanism is shown in Fig. 13.

Overall, we observe that, there is significant reduction in the production from community-owned PV because of curtailment due to voltage constraints. This reduces the financial benefits offered by the community-owned assets and limits the assets that can be further included in the network. Hence, the study shows that when the network (grid) constraints are incorporated then the benefits from the community assets are reduced. Therefore, when considering community assets, one should pay attention to the location of the assets and nature of the distribution grid considered. If the community assets are placed in a location where there is no grid issue, then there is a higher benefit.

While considering the network constraints, even though the benefits from the community-owned assets are reduced due to curtailment, still community-owned assets provide a substantially lower annual bill for both the fixed tariff and ToU tariff pricing schemes (as shown in Table 4 & 5). Furthermore, these economic results were obtained with the same unitary cost of the assets for the community-owned as for individually-owned, which might not be the case in real-world scenario, whereas in practice, the unitary cost of

the community-owned asset might be lower due to economies of the scale effect. Thus, more savings can be obtained from community-owned assets by considering the economies of scale in the unitary cost of the assets. Therefore, community assets generate benefits to the community. A key research question that still remains is how to redistribute fairly these benefits to the community members. This will be addressed next, in Section IV-D.

D. FAIR REDISTRIBUTION OF BENEFITS ACHIEVED FROM COMMUNITY-OWNED ASSETS

For both the cases with and without network constraints, results from the economic analysis described in Section IV-C show that community-owned assets lead to reduction in the annual electricity bill compared to individually-owned assets. Hence, individual agents can achieve more savings (higher benefits) by forming the community coalition and by investing in jointly-owned assets. In this section, in order to fairly redistribute the benefits obtained from community-owned assets to individual agents, we implement the redistribution scheme introduced in Section III-E that utilizes the marginal contribution principle (a key concept from coalitional game theory). First, we implement for the case with community-owned generator only, without storage asset. Then, redistribution of cost savings from both the community-owned generator and storage is implemented.

1) REDISTRIBUTION OF BENEFITS FROM COMMUNITY RENEWABLE GENERATOR ASSET ONLY WITHOUT BATTERY

The investment cost of community PV was assumed to be shared equally among the agents, but the revenues are not equally distributed. As described in Section III-E2, using Eq. (32) the new yearly energy bills ($b_i^{*(NC)}(T)$) of individual agents after redistribution of community savings from a community-owned solar PV is computed by marginal cost redistribution method with network constraints. This method is the approximated version that is computationally tractable. The new yearly bills obtained using approximated marginal cost redistribution method are compared with the new yearly bills obtained using marginal cost redistribution method without approximation. The comparison between the redistribution mechanism *with approximation* and *without approximation* is shown in Fig. 14 for the fixed tariff and Fig. 15 for the dynamic ToU Tariff.

For fixed tariff, the individual agents yearly bills obtained after redistribution by approximated marginal cost redistribution method is similar to results obtained by redistribution mechanism without approximation, with the correlation coefficient of 99.99% (as shown by Fig. 14). Similarly, for dynamic ToU tariff the results are similar with the correlation coefficient of 99.98% (as shown by Fig. 15). Hence, while considering the network constraints, approximated marginal cost redistribution method can be used to redistribute the benefits from community owned assets, as it is much more

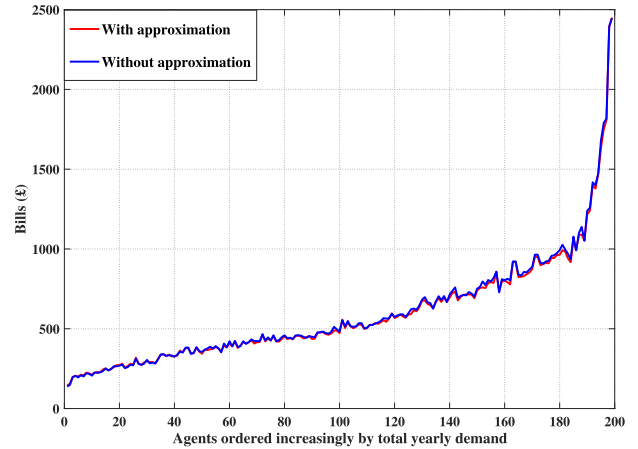


FIGURE 14. Comparison between the individual agents yearly bills obtained after redistribution by approximated marginal cost redistribution method with redistribution mechanism without approximation for a fixed tariff of 16 pence/kWh.

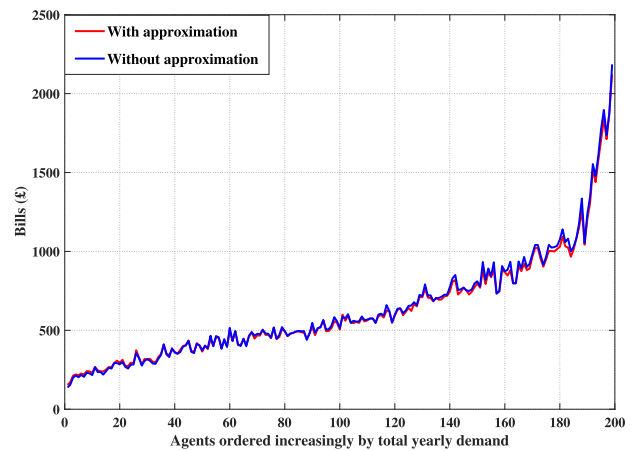


FIGURE 15. Comparison between the individual agents yearly bills obtained after redistribution by approximated marginal cost redistribution method with redistribution mechanism without approximation for the dynamic ToU Agile Octopus tariff.

computationally tractable. In Fig. 14 & 15, on the X-axis we order the 200 agents (households) of the considered community in increasing order by their total annual energy consumption. The Y-axis gives the annual energy bill of each agent. This representation is useful to evaluate the economic fairness in the redistribution scheme among the small and larger consumers.

In order to test the advantages of the proposed redistribution mechanism the marginal cost redistribution method with network constraints, we compare its benefits with the instantaneous power redistribution method that was described in Section III-E3 which corresponds to the state-of-the-art redistribution mechanism (based on current practice).

Fig. 16 shows the individual agents annual bills after redistribution by marginal cost redistribution method and instantaneous power redistribution method in the case of the dynamic ToU Agile Octopus [91] tariff pricing scheme. The crossover point between the redistributed bill curves in Fig. 16 clearly shows that, with marginal cost redistribution method 67% of

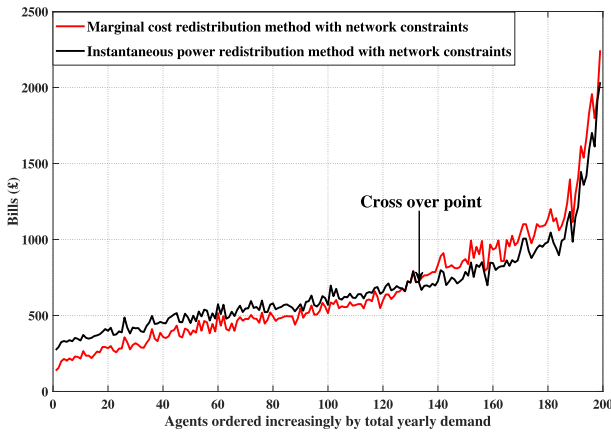


FIGURE 16. Individual agents yearly bills after redistribution by marginal cost redistribution method and instantaneous power redistribution method, with network constraints for the dynamic ToU Agile Octopus tariff.

the agents can achieve lower annual bill than instantaneous power redistribution method (these are the lower total annual bill, hence smaller consumers), while with state-of-the-art method only 33% of the agents obtain lower annual bills (hence this scheme benefits mainly larger consumers, with larger annual demand). Hence, under the proposed marginal cost redistribution method with network constraints, more agents are able to decrease their annual bill than the instantaneous power redistribution method with network constraints.

While it is true that large consumers benefit slightly less under our scheme (because, of course, the total community bill is equal in both cases), these agents with higher demand profiles are the agents who already obtain the highest bill reduction as compared to agents with lower demand profiles as illustrated in the Fig. 17. Therefore, the proposed redistribution mechanism achieves a fairer redistribution as compared to currently practised redistribution scheme. Practically, having the 67% of agents in the community (including many smaller consumers) also benefiting from the proposed redistribution mechanism would lead to greater social acceptance, and hence more likely to join the coalition to invest in the jointly-owned community assets.

2) REDISTRIBUTION OF BENEFITS FROM BOTH THE COMMUNITY RENEWABLE GENERATOR AND BATTERY STORAGE ASSETS

In this scenario, the savings (benefits) achieved from both the community-owned solar PV and community-owned battery are redistributed by marginal cost redistribution method with network constraints only. Investment costs for the community energy assets were shared equally among the agents. Fig. 18 shows the individual agents annual bills after redistribution in the case of the dynamic ToU Agile Octopus [91] tariff pricing scheme.

In the literature, the instantaneous power redistribution method is only used for solar power or wind, but it cannot be used for communities with batteries, as it is not easy to determine who used more the battery assets than others.

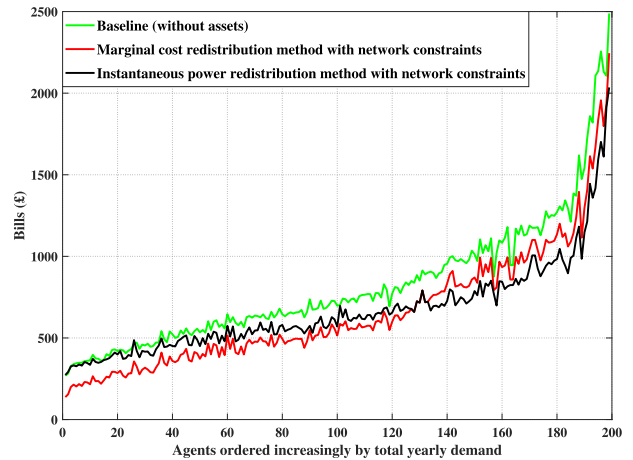


FIGURE 17. Individual agents yearly bills without assets (baseline), and yearly bills after redistribution by marginal cost redistribution method and instantaneous power redistribution method, with network constraints for the dynamic ToU Agile Octopus tariff.

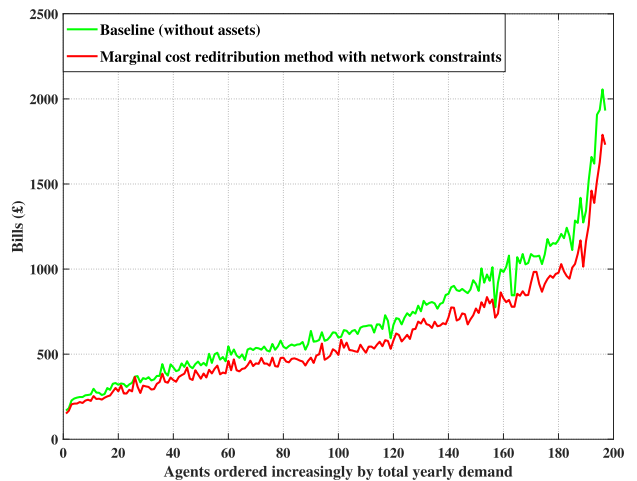


FIGURE 18. Individual agents yearly bills without assets (baseline) and yearly bills after redistribution by marginal cost redistribution method with network constraints for the dynamic ToU Agile Octopus tariff.

This is another key point that demonstrates the advantages of the proposed redistribution mechanism based on marginal contribution. Yet, there is still a need to redistribute fairly the benefits obtained from jointly-owned community renewable generator and storage assets. Hence, the proposed marginal cost redistribution method based on individual agents marginal contribution provides the equal and fair mechanism to redistribute the energy outputs (and hence financial benefits) from both the jointly-owned community solar PV and battery assets.

V. CONCLUSION

In this paper, we have proposed a techno-economic modeling methodology that couple's battery control, battery degradation, community energy from RES with LV network operating constraints, with a fair redistribution optimisation of benefits to jointly owned assets. The control mechanism was implemented for both fixed electricity tariffs

and dynamic ToU tariffs to compare the benefits obtained when an individual household invest in their own energy assets versus investing jointly in a community-owned energy assets. To compare the economic performance of investments in community-owned assets and individually-owned assets, we considered an energy community of two hundred prosumers, that were all modelled by real time-series data of generation and consumption profiles from a community in UK for a full year. We computed yearly bills resulting from the proposed battery control algorithm and compared the yearly bills computed with and without network constraints to assess how network/grid constraints can impact the deployment of individual and community-owned assets.

Experimental results from our study (based on real input data from the UK) show that, overall, the operation of individually-owned distributed assets are less impacted by grid constraints than the operation of community-owned assets. Indeed, when generation is not located close enough to consumption, it might lead to local over-voltage that could result in curtailment by the distribution system operator of export from community-owned assets. This curtailment reduces the overall saving of the community, which illustrates the importance of considering the physical grid constraints in the energy community schemes. However, even with curtailment due to grid constraints, the economic comparison between community-owned assets and individually-owned assets still shows that community-owned assets provides better benefits to energy communities for both tariffs schemes studied.

Next, for energy communities with community-owned assets, we developed a practically applicable and computationally efficient redistribution mechanism to fairly share the energy and associated financial benefits from community-owned assets between the community members. This redistribution mechanism is based on the marginal contribution of each member, which is a key concept from coalitional game theory that looks at rewarding members based on the value they provide to the community. We showed that the proposed redistribution mechanism is applicable to any type of community-owned assets, even storage assets; despite the apparent difficulty to assess how each member takes advantage of assets.

Future work will focus on extending the model to consider new revenue flows for an energy community through participation in the energy and ancillary services markets, such as providing demand-side flexibility services to the distribution system operator. Another extension is to assess how peer-to-peer market mechanisms with individually owned assets can increase the benefits of such community energy scheme, and how such a setting compares to community-owned assets. We will also consider extensions of our model that take into account other energy vectors and assets - such as transport and community-shared hydrogen fuel cells. In this context, green hydrogen is increasingly being explored as a promising energy storage solution, for renewable communities with

excess renewable generation, such as those on the Orkney Islands [98], [99].

Finally, on the more theoretical side, development of other redistribution schemes that closely resemble or approximate the Shapley value solution concept, but are computationally tractable to compute, forms another exciting area of research.

REFERENCES

- [1] UN Sustainable Development Goals. *Goal 7: Affordable and Clean Energy*. Accessed: Jun. 24, 2020. [Online]. Available: <https://www.un.org/sustainabledevelopment/energy/>
- [2] Intergovernmental Panel on Climate Change (IPCC) Report. *2019-IPCC*. Accessed: Jun. 24, 2020. [Online]. Available: <https://www.ipcc.ch/2019/>
- [3] UK, Energy and Industrial Strategy, "Energy white paper: Powering our net zero future," Dept. Bus., Energy Ind. Strategy, U.K., Tech. Rep. CCS0220144090, CP 337, Dec. 2020. [Online]. Available: http://www.ret.gov.au/energy/facts/white_paper/Pages/energy_white_paper.aspx
- [4] Our World in Data. *Renewable Energy*. Accessed: May 25, 2020. [Online]. Available: <https://ourworldindata.org/renewable-energy>
- [5] Y. Zhou, J. Wu, and C. Long, "Evaluation of peer-to-peer energy sharing mechanisms based on a multiagent simulation framework," *Appl. Energy*, vol. 222, pp. 993–1022, Jul. 2018.
- [6] J. Guerrero, A. C. Chapman, and G. Verbi, "Decentralized P2P energy trading under network constraints in a low-voltage network," *IEEE Trans. Smart Grid*, vol. 10, no. 5, pp. 5163–5173, Sep. 2018.
- [7] S. Dong, E. Kremers, M. Brucoli, R. Rothman, and S. Brown, "Improving the feasibility of household and community energy storage: A techno-enviro-economic study for the UK," *Renew. Sustain. Energy Rev.*, vol. 131, Oct. 2020, Art. no. 110009. [Online]. Available: <https://www.sciencedirect.com/science/article/pii/S1364032120303002>
- [8] European Commission. (2015). *Best practices on Renewable Energy Self-consumption, SWD 141 Final, Brussels*. [Online]. Available: https://ec.europa.eu/energy/sites/ener/files/documents/1_EN_autre_document_travail_service_part1_v6.pdf
- [9] Community Energy Scotland. *Community Energy Projects & Innovations*. Accessed: Jun. 15, 2020. [Online]. Available: <https://www.communityenergyscotland.org.uk/projects.asp>
- [10] E. Mengelkamp, J. Gärtner, K. Rock, S. Kessler, L. Orsini, and C. Weinhardt, "Designing microgrid energy markets: A case study: The Brooklyn microgrid," *Appl. Energy*, vol. 210, pp. 870–880, Jan. 2018.
- [11] A. Caramizaru and A. Uihlein, *Energy Communities: An Overview of Energy and Social Innovation*, vol. 30083. Luxembourg City, Luxembourg: Publication Office European Union, 2020.
- [12] Findhorn Ecovillage. *Community-Owned Wind Turbines, Findhorn Wind Park*. Accessed: Jun. 16, 2020. [Online]. Available: <https://ecovillagefindhorn.org/index.php/renewable>
- [13] SSEN, ANM. *Orkney ANM Live*. Accessed: May 25, 2021. [Online]. Available: <https://www.ssen.co.uk/ANMGeneration/>
- [14] S. Dong, E. Kremers, M. Brucoli, R. Rothman, and S. Brown, "Techno-enviro-economic assessment of household and community energy storage in the UK," *Energy Convers. Manage.*, vol. 205, Feb. 2020, Art. no. 112330. [Online]. Available: <https://www.sciencedirect.com/science/article/pii/S0196890419313378>
- [15] S. van der Stelt, T. AISkaif, and W. van Sark, "Techno-economic analysis of household and community energy storage for residential prosumers with smart appliances," *Appl. Energy*, vol. 209, pp. 266–276, Jan. 2018. [Online]. Available: <https://www.sciencedirect.com/science/article/pii/S0306261917315337>
- [16] E. Barbour, D. Parra, Z. Awwad, and M. C. González, "Community energy storage: A smart choice for the smart grid?" *Appl. Energy*, vol. 212, pp. 489–497, Feb. 2018. [Online]. Available: <https://www.sciencedirect.com/science/article/pii/S0306261917317713>
- [17] A. Walker and S. Kwon, "Analysis on impact of shared energy storage in residential community: Individual versus shared energy storage," *Appl. Energy*, vol. 282, Jan. 2021, Art. no. 116172. [Online]. Available: <https://www.sciencedirect.com/science/article/pii/S0306261920315749>
- [18] G. Chalkiadakis, E. Elkind, and M. Wooldridge, "Computational aspects of cooperative game theory," *Synth. Lectures Artif. Intell. Mach. Learn.*, vol. 5, no. 6, pp. 1–168, Oct. 2011.

- [19] M. Alam, S. D. Ramchurn, and A. Rogers, "Cooperative energy exchange for the efficient use of energy and resources in remote communities," in *Proc. 12th Int. Conf. Auto. Agents Multiagent Syst. (AAMAS)*, vol. 2, 2013, pp. 731–738.
- [20] S. S. Fatima, M. Wooldridge, and N. R. Jennings, "A linear approximation method for the Shapley value," *Artif. Intell.*, vol. 172, no. 14, pp. 1673–1699, Sep. 2008.
- [21] S. Norbu, B. Couraud, V. Robu, M. Andoni, and D. Flynn, "Modelling the redistribution of benefits from joint investments in community energy projects," *Appl. Energy*, vol. 287, Apr. 2021, Art. no. 116575. [Online]. Available: <https://www.sciencedirect.com/science/article/pii/S03062619211001215>
- [22] European Marine Energy Centre (EMEC). *ReFLEX: Responsive FLEXibilities for Orkney Islands*. Accessed: May 25, 2020. [Online]. Available: <http://www.emec.org.uk/ukri-gives-green-light-to-reflex-orkney-project-2/>
- [23] V. Z. Gjorgievski, S. Cundeve, and G. E. Georghiou, "Social arrangements, technical designs and impacts of energy communities: A review," *Renew. Energy*, vol. 169, pp. 1138–1156, May 2021. [Online]. Available: <https://www.sciencedirect.com/science/article/pii/S09601481211000859>
- [24] G. Seyfang, J. J. Park, and A. Smith, "A thousand flowers Blooming? An examination of community energy in the UK," *Energy Policy*, vol. 61, pp. 977–989, Oct. 2013.
- [25] P. Hansen, "Optimising shared renewable energy systems: An institutional approach," *Energy Res. Social Sci.*, vol. 73, Mar. 2021, Art. no. 101953. [Online]. Available: <https://www.sciencedirect.com/science/article/pii/S22146296211000463>
- [26] R. J. Hewitt, N. Bradley, A. B. Compagnucci, C. Barlagne, A. Ceglaz, R. Cremades, M. McKeen, I. M. Otto, and B. Slee, "Social innovation in community energy in Europe: A review of the evidence," *Frontiers Energy Res.*, vol. 7, p. 31, Apr. 2019.
- [27] D. N.-Y. Mah, "Community solar energy initiatives in urban energy transitions: A comparative study of Foshan, China and Seoul, South Korea," *Energy Res. Social Sci.*, vol. 50, pp. 129–142, Apr. 2019.
- [28] S. Becker, C. Kunze, and M. Vancea, "Community energy and social entrepreneurship: Addressing purpose, organisation and embeddedness of renewable energy projects," *J. Cleaner Prod.*, vol. 147, pp. 25–36, Mar. 2017.
- [29] T. Hargreaves, S. Hielscher, G. Seyfang, and A. Smith, "Grassroots innovations in community energy: The role of intermediaries in niche development," *Global Environ. Change*, vol. 23, no. 5, pp. 868–880, Oct. 2013.
- [30] P. McCallum, D. P. Jenkins, A. D. Peacock, S. Patidar, M. Andoni, D. Flynn, and V. Robu, "A multi-sectoral approach to modelling community energy demand of the built environment," *Energy Policy*, vol. 132, pp. 865–875, Sep. 2019. [Online]. Available: <https://www.sciencedirect.com/science/article/pii/S0301421519304112>
- [31] T. Bauwens and P. Devine-Wright, "Positive energies? An empirical study of community energy participation and attitudes to renewable energy," *Energy Policy*, vol. 118, pp. 612–625, Jul. 2018.
- [32] T. Bauwens, "Analyzing the determinants of the size of investments by community renewable energy members: Findings and policy implications from Flanders," *Energy Policy*, vol. 129, pp. 841–852, Jun. 2019.
- [33] V. Robu, D. Flynn, M. Andoni, and M. Mokhtar, "Consider ethical and social challenges in smart grid research," *Nature Mach. Intell.*, vol. 1, no. 12, pp. 548–550, Dec. 2019.
- [34] Z. Huang, H. Yu, Z. Peng, and M. Zhao, "Methods and tools for community energy planning: A review," *Renew. Sustain. Energy Rev.*, vol. 42, pp. 1335–1348, Feb. 2015.
- [35] G. Mendes, C. Ioakimidis, and P. Ferrão, "On the planning and analysis of integrated community energy systems: A review and survey of available tools," *Renew., Sustain. Energy Rev.*, vol. 15, no. 9, pp. 4836–4854, Dec. 2011.
- [36] V. Robu, G. Chalkiadakis, R. Kota, A. Rogers, and N. R. Jennings, "Rewarding cooperative virtual power plant formation using scoring rules," *Energy*, vol. 117, pp. 19–28, Dec. 2016.
- [37] A. Hany Elgamal, G. Kocher-Oberlehner, V. Robu, and M. Andoni, "Optimization of a multiple-scale renewable energy-based virtual power plant in the UK," *Appl. Energy*, vol. 256, Dec. 2019, Art. no. 113973. [Online]. Available: <https://www.sciencedirect.com/science/article/pii/S030626191919316605>
- [38] G. Chalkiadakis, V. Robu, R. Kota, A. Rogers, and N. Jennings, "Cooperatives of distributed energy resources for efficient virtual power plants," in *Proc. 10th Int. Conf. Auto. Agents Multiagent Syst. (AAMAS)*, May 2011, pp. 787–794.
- [39] R. Kota, G. Chalkiadakis, V. Robu, A. Rogers, and N. R. Jennings, "Cooperatives for demand side management," in *Proc. 7th Conf. Prestigious Appl. Intell. Syst. (PAIS @ ECAI)*, Aug. 2012, pp. 969–974. [Online]. Available: <https://eprints.soton.ac.uk/339761/>
- [40] I. Antonopoulos, V. Robu, B. Couraud, and D. Flynn, "Data-driven modelling of energy demand response behaviour based on a large-scale residential trial," *Energy AI*, vol. 4, Jun. 2021, Art. no. 100071. [Online]. Available: <https://www.sciencedirect.com/science/article/pii/S2666546821000252>
- [41] I. Antonopoulos, V. Robu, B. Couraud, D. Kirli, S. Norbu, A. Kiprakis, D. Flynn, S. Elizondo-Gonzalez, and S. Wattam, "Artificial intelligence and machine learning approaches to energy demand-side response: A systematic review," *Renew. Sustain. Energy Rev.*, vol. 130, Sep. 2020, Art. no. 109899. [Online]. Available: <https://www.sciencedirect.com/science/article/pii/S136403212030191X>
- [42] H. Ma, V. Robu, N. Li, and D. C. Parkes, "Incentivizing reliability in demand-side response," in *Proc. IJCAI 25th Int. Joint Conf. Artif. Intell.*, Apr. 2016, pp. 352–358.
- [43] H. Ma, D. C. Parkes, and V. Robu, "Generalizing demand response through reward bidding," in *Proc. 16th Conf. Auton. Agents MultiAgent Syst. (International Foundation for Autonomous Agents and Multiagent Systems)*, 2017, pp. 60–68.
- [44] R. Meir, H. Ma, and V. Robu, "Contract design for energy demand response," in *Proc. 26th Int. Joint Conf. Artif. Intell.*, Aug. 2017, pp. 1202–1208, doi: 10.24963/ijcai.2017/167.
- [45] V. Robu, M. Vinyals, A. Rogers, and N. R. Jennings, "Efficient buyer groups with Prediction-of-Use electricity tariffs," *IEEE Trans. Smart Grid*, vol. 9, no. 5, pp. 4468–4479, Sep. 2018.
- [46] M. Andoni, V. Robu, W.-G. Früh, and D. Flynn, "Game-theoretic modeling of curtailment rules and network investments with distributed generation," *Appl. Energy*, vol. 201, pp. 174–187, Sep. 2017.
- [47] M. Andoni, V. Robu, B. Couraud, W.-G. Früh, S. Norbu, and D. Flynn, "Analysis of strategic renewable energy, grid and storage capacity investments via Stackelberg-cournot modelling," *IEEE Access*, vol. 9, pp. 37752–37771, 2021.
- [48] B. Couraud, S. Norbu, M. Andoni, V. Robu, H. Gharavi, and D. Flynn, "Optimal residential battery scheduling with asset lifespan consideration," in *Proc. IEEE PES Innov. Smart Grid Technol. Eur. (ISGT-Europe)*, Oct. 2020, pp. 630–634.
- [49] M. Andoni, W. Tang, V. Robu, and D. Flynn, "Data analysis of battery storage systems," *CIREN-Open Access Proc. J.*, vol. 2017, no. 1, pp. 96–99, Oct. 2017.
- [50] D. Roman, S. Saxena, V. Robu, M. Pecht, and D. Flynn, "Machine learning pipeline for battery state-of-health estimation," *Nature Mach. Intell.*, vol. 3, no. 5, pp. 447–456, May 2021.
- [51] V. Robu, E. H. Gerding, S. Stein, D. C. Parkes, A. Rogers, and N. R. Jennings, "An online mechanism for multi-unit demand and its application to plug-in hybrid electric vehicle charging," *J. Artif. Intell. Res.*, vol. 48, pp. 175–230, Oct. 2013.
- [52] C. Etukudor, B. Couraud, V. Robu, W.-G. Früh, D. Flynn, and C. Okereke, "Automated negotiation for Peer-to-Peer electricity trading in local energy markets," *Energies*, vol. 13, no. 4, p. 920, Feb. 2020. [Online]. Available: <https://www.mdpi.com/1996-1073/13/4/920>
- [53] M. Andoni, V. Robu, and D. Flynn, "Blockchains: Crypto-control your own energy supply," *Nature*, vol. 548, no. 7666, p. 158, Aug. 2017.
- [54] M. Andoni, V. Robu, D. Flynn, S. Abram, D. Geach, D. Jenkins, P. McCallum, and A. Peacock, "Blockchain technology in the energy sector: A systematic review of challenges and opportunities," *Renew. Sustain. Energy Rev.*, vol. 100, pp. 143–174, Feb. 2019.
- [55] K. Pumphrey, S. L. Walker, M. Andoni, and V. Robu, "Green hope or red herring? Examining consumer perceptions of peer-to-peer energy trading in the United Kingdom," *Energy Res. Social Sci.*, vol. 68, Oct. 2020, Art. no. 101603.
- [56] B. P. Koirala, E. van Oost, and H. van der Windt, "Community energy storage: A responsible innovation towards a sustainable energy system?" *Appl. Energy*, vol. 231, pp. 570–585, Dec. 2018.
- [57] J. Sardi and N. Mithulanathan, "Community energy storage, a critical element in smart grid: A review of technology, prospect, challenges and opportunity," in *Proc. 4th Int. Conf. Eng. Technol. Technopreneuship (ICE2T)*, Aug. 2014, pp. 125–130.
- [58] D. Strickland, M. A. Varnosfederani, J. Scott, P. Quintela, A. Duran, R. Bravery, A. Corliss, K. Ashworth, and S. Blois-Brooke, "A review of community electrical energy systems," in *Proc. IEEE Int. Conf. Renew. Energy Res. Appl. (ICRERA)*, Nov. 2016, pp. 49–54.

- [59] D. Parra, S. A. Norman, G. S. Walker, and M. Gillott, "Optimum community energy storage for renewable energy and demand load management," *Appl. Energy*, vol. 200, pp. 358–369, Aug. 2017.
- [60] M. Elkazaz, M. Sumner, E. Naghiyev, Z. Hua, and D. W. P. Thomas, "Techno-economic sizing of a community battery to provide community energy billing and additional ancillary services," *Sustain. Energy, Grids Netw.*, vol. 26, Jun. 2021, Art. no. 100439. [Online]. Available: <https://www.sciencedirect.com/science/article/pii/S2352467721000102>
- [61] D. Parra, S. A. Norman, G. S. Walker, and M. Gillott, "Optimum community energy storage for renewable energy and demand load management," *Appl. Energy*, vol. 200, pp. 358–369, Aug. 2017. [Online]. Available: <https://www.sciencedirect.com/science/article/pii/S0306261917305524>
- [62] D. Parra, M. Gillott, S. A. Norman, and G. S. Walker, "Optimum community energy storage system for PV energy time-shift," *Appl. Energy*, vol. 137, pp. 576–587, Jan. 2015. [Online]. Available: <https://www.sciencedirect.com/science/article/pii/S030626191400871X>
- [63] M. A. Hossain, R. K. Chakraborty, M. J. Ryan, and H. R. Pota, "Energy management of community energy storage in grid-connected microgrid under uncertain real-time prices," *Sustain. Cities Soc.*, vol. 66, Mar. 2021, Art. no. 102658. [Online]. Available: <https://www.sciencedirect.com/science/article/pii/S221067072030874X>
- [64] J. Sardi, N. Mithulananthan, M. M. Islam, and C. K. Gan, "Framework of virtual microgrids formation using community energy storage in residential networks with rooftop photovoltaic units," *J. Energy Storage*, vol. 35, Mar. 2021, Art. no. 102250. [Online]. Available: <https://www.sciencedirect.com/science/article/pii/S2352152X21000190>
- [65] D. Gebbran, S. Mhanna, Y. Ma, A. C. Chapman, and G. Verbi, "Fair coordination of distributed energy resources with volt-var control and PV curtailment," *Appl. Energy*, vol. 286, Mar. 2021, Art. no. 116546. [Online]. Available: <https://www.sciencedirect.com/science/article/pii/S0306261921000933>
- [66] J. Guerrero, B. Sok, A. C. Chapman, and G. Verbi, "Electrical-distance driven peer-to-peer energy trading in a low-voltage network," *Appl. Energy*, vol. 287, Apr. 2021, Art. no. 116598. [Online]. Available: <https://www.sciencedirect.com/science/article/pii/S0306261921001380>
- [67] B. Wang, G. Verbi, and W. Xiao, "Power sharing in an islanded LV distribution network fully installed with PV-battery systems based on grid-forming control," in *Proc. Int. Conf. Smart Grids Energy Syst. (SGES)*, Nov. 2020, pp. 459–464.
- [68] M. I. Azim, W. Tushar, and T. K. Saha, "Investigating the impact of P2P trading on power losses in grid-connected networks with prosumers," *Appl. Energy*, vol. 263, Apr. 2020, Art. no. 114687. [Online]. Available: <https://www.sciencedirect.com/science/article/pii/S0306261920301999>
- [69] M. Mokhtar, V. Robu, D. Flynn, C. Higgins, J. Whyte, C. Loughran, and F. Fulton, "Automating the verification of the low voltage network cables and topologies," *IEEE Trans. Smart Grid*, vol. 11, no. 2, pp. 1657–1666, Mar. 2020.
- [70] B. Couraud, P. Kumar, V. Robu, D. Jenkins, S. Norbu, D. Flynn, and A. R. Abhyankar, "Assessment of decentralized reactive power control strategies for low voltage PV inverters," in *Proc. 8th Int. Conf. Power Syst. (ICPS)*, Dec. 2019, pp. 1–6.
- [71] G. Tévar-Bartolomé, A. Gómez-Expósito, A. Arcos-Vargas, and M. Rodríguez-Montañés, "Network impact of increasing distributed PV hosting: A utility-scale case study," *Sol. Energy*, vol. 217, pp. 173–186, Mar. 2021. [Online]. Available: <https://www.sciencedirect.com/science/article/pii/S0038092X2100092X>
- [72] M. Grzanić, J. M. Morales, S. Pineda, and T. Capuder, "Electricity cost-sharing in energy communities under dynamic pricing and uncertainty," *IEEE Access*, vol. 9, pp. 30225–30241, 2021.
- [73] C. B. Heendeniya, "Agent-based modeling of a rule-based community energy sharing concept," in *Proc. E3S Web Conf.*, vol. 239, 2021, pp. 1–10. [Online]. Available: <https://doi.org/10.1051/e3sconf/202123900001>
- [74] M. Moncecchi, S. Meneghello, and M. Merlo, "A game theoretic approach for energy sharing in the Italian renewable energy communities," *Appl. Sci.*, vol. 10, no. 22, p. 8166, 2020.
- [75] L. Li, "Optimal coordination strategies for load service entity and community energy systems based on centralized and decentralized approaches," *Energies*, vol. 13, no. 12, p. 3202, 2020.
- [76] P. Chakraborty, E. Baeyens, K. Poolla, P. P. Khargonekar, and P. Varaiya, "Sharing storage in a smart grid: A coalitional game approach," *IEEE Trans. Smart Grid*, vol. 10, no. 4, pp. 4379–4390, Jul. 2019.
- [77] M. Marzband, R. R. Ardeshiri, M. Moafi, and H. Uppal, "Distributed generation for economic benefit maximization through coalition formation-based game theory concept," *Int. Trans. Elect. Energy Syst.*, vol. 27, no. 6, p. e2313, Jun. 2017.
- [78] I. Abada, A. Ehrenmann, and X. Lambin, "On the viability of energy communities," *Energy J.*, vol. 41, no. 1, pp. 113–150, Jan. 2020. [Online]. Available: <https://ezproxy1.hw.ac.uk/login?url=http://search.ebscohost.com/login.aspx?direct=true&db=buh&AN=140081319&site=ehost-live,doi:10.2171/01956574.41.1.iaba>
- [79] A. Chis and V. Koivunen, "Coalitional game-based cost optimization of energy portfolio in smart grid communities," *IEEE Trans. Smart Grid*, vol. 10, no. 2, pp. 1960–1970, Mar. 2019.
- [80] C. Feng, F. Wen, S. You, Z. Li, F. Shahnia, and M. Shahidepour, "Coalitional game-based transactive energy management in local energy communities," *IEEE Trans. Power Syst.*, vol. 35, no. 3, pp. 1729–1740, May 2020.
- [81] X. Liu, S. Wang, and J. Sun, "Energy management for community energy network with CHP based on cooperative game," *Energies*, vol. 11, no. 5, p. 1066, 2018.
- [82] Y. Yang, G. Hu, and C. J. Spanos, "Optimal sharing and fair cost allocation of community energy storage," 2020, *arXiv:2010.15455*. [Online]. Available: <http://arxiv.org/abs/2010.15455>
- [83] UKERC Energy Data Centre. *Thames Valley Vision End Point Monitor Data*. Accessed: May 11, 2020. [Online]. Available: <http://www.thamesvalleyvision.co.uk/>
- [84] IEEE 13-Bus Feeder. *Resources | PES Test Feeder*. Accessed: Jan. 3, 2020. [Online]. Available: <https://site.ieee.org/pes-testfeeders/resources/>
- [85] Met Office. (2019). *MIDAS Open:UK Hourly Solar Radiation Data, V201901*. Centre for Environmental Data Analysis, 01 March 2019. Accessed: Feb. 15, 2021. [Online]. Available: <http://data.ceda.ac.uk/badc/ukmo-midas-open/data/uk-radiation-dataset-version-201901/orkney>
- [86] K. Movassagh, A. Raihan, B. Balasingam, and K. Pattipati, "A critical look at Coulomb counting approach for state of charge estimation in batteries," *Energies*, vol. 14, no. 14, p. 4074, 2021.
- [87] ABB. *UPS and Power Conditioning | ABB*. Accessed: Jul. 12, 2021. [Online]. Available: <https://new.abb.com/ups>
- [88] The Office of Gas and Electricity Markets (Ofgem). *About the FIT Scheme Closure of the FIT Scheme*. Accessed: May 23, 2020. [Online]. Available: <https://www.ofgem.gov.uk/environmental-programmes/fit/about-fit-scheme>
- [89] Money Supermarket. *Fixed-Price Electricity Tariffs Comparison*. Accessed: Feb. 11, 2020. [Online]. Available: <https://www.moneysupermarket.com/gas-and-electricity/compare-electricity-prices/>
- [90] The Office of Gas and Electricity Markets (Ofgem). *Compare Gas and Electricity Tariffs: Ofgem-Accredited Price Comparison Sites*. Accessed: Apr. 15, 2020. [Online]. Available: <https://www.ofgem.gov.uk/information-consumers/energy-advice-households/switching-energy-tariff-or-supplier>
- [91] Octopus Energy. *Agile Octopus Tariff*. Accessed: Feb. 11, 2020. [Online]. Available: <https://octopus.energy/agile/>
- [92] C. Long, J. Wu, C. Zhang, L. Thomas, M. Cheng, and N. Jenkins, "Peer-to-peer energy trading in a community microgrid," in *Proc. IEEE Power Energy Soc. Gen. Meeting*, Jul. 2017, pp. 1–5.
- [93] K. Curry, "Lithium-ion battery costs and market squeezed margins seek technology improvements & new business models," Bloomberg, London, U.K., BNEF Rep., Jul. 2017. [Online]. Available: <https://data.bloomberglp.com/bnef/sites/14/2017/07/BNEF-Lithium-ion-battery-costs-and-market.pdf>
- [94] BloombergNEF. *Battery Pack Prices Fall as Market Ramps up With Market Average at \$156/kWh In 2019*. Accessed: Dec. 16, 2020. [Online]. Available: <https://about.bnef.com/blog/battery-pack-prices-fall-as-market-ramps-up-with-market-average-at-156-kwh-in-2019/>
- [95] PV Europe. *Price of Li-Ion Batteries for Vehicles Below 200 USD/kWh in 2019*. Accessed: Dec. 9, 2020. <https://www.pveurope.eu/energy-storage/price-li-ion-batteries-vehicles-below-200-usd-kwh-2019>
- [96] R. Hensley, J. Newman, and M. Rogers, "Battery technology charges ahead," in *Sustainability & Resource Productivity*. New York, NY, USA: McKinsey & Company, Jul. 2012. [Online]. Available: <http://www.mckinsey.com/business-functions/sustainability-and-resource-productivity/our-insights/battery-technology-charges-ahead>
- [97] EIA. (2020). *Cost and Performance Characteristics of New Generating Technologies, Annual Energy Outlook 2020*. [Online]. Available: https://www.eia.gov/outlooks/aeo/assumptions/pdf/table_8.2.pdf
- [98] G. Zhao, E. R. Nielsen, E. Troncoso, K. Hyde, J. S. Romeo, and M. Diderich, "Life cycle cost analysis: A case study of hydrogen energy application on the Orkney Islands," *Int. J. Hydrogen Energy*, vol. 44, no. 19, pp. 9517–9528, Apr. 2019. [Online]. Available: <https://www.sciencedirect.com/science/article/pii/S0360319918325035>
- [99] B. Widera, "Renewable hydrogen implementations for combined energy storage, transportation and stationary applications," *Thermal Sci. Eng. Prog.*, vol. 16, May 2020, Art. no. 100460. [Online]. Available: <https://www.sciencedirect.com/science/article/pii/S2451904919302628>



SONAM NORBU (Member, IEEE) received the Bachelor of Engineering degree in electrical engineering from the College of Science and Technology (CST), Royal University of Bhutan (RUB), in 2007, and the Master of Engineering degree in power electronics and drives from the Hindustan Institute of Technology and Science, Hindustan University, India, in 2010. He is currently pursuing the Ph.D. degree with the Smart Systems Group, School of Engineering and Physical Sciences,

Institute of Sensors, Signals and Systems, Heriot-Watt University, Edinburgh, U.K.

His Ph.D. research is focused on exploring the issues of enabling resilient energy communities or local microgrids using the tools from distributed AI (specifically multi-agent systems) and cooperative game theory. He lectures at CST, RUB.



BENOIT COURAUD (Member, IEEE) received the engineering degree from the Ecole Centrale de Lyon, Ecully, France, in 2009, and the M.Sc. degree in electronic and electrical engineering from Shanghai Jiao Tong University, China, in 2009.

His Ph.D. research focused on radio frequency identification power transfer optimization at ISEN, Toulon, France, and the IM2NP Laboratory, University of Aix Marseille, Marseille, France. He is currently a Research Associate with Heriot Watt University, working on artificial intelligence, local electricity market solutions and optimization tools for renewable energy integration, and smart grids operations.



VALENTIN ROBU is a Senior Research Scientist at CWI, National Research Institute for Mathematics and Computer Science, Amsterdam, and a part-time Associate Professor at TU Delft, The Netherlands. Before October 2020, he was an Associate Professor at Heriot-Watt University, Edinburgh, Scotland, U.K., where he still holds a visiting appointment. He is also a Research Affiliate at the Center for Collective Intelligence, Massachusetts Institute of Technology (MIT), USA.

Prior to this, he was a Senior Research Fellow at the University of Southampton, U.K., and a Visiting Scholar with the Computer Science Department, Harvard University, USA. He has published over 150 papers in top-ranked journals, conferences, and edited volumes, in both the areas of artificial intelligence and electrical engineering. He is a Co-Investigator in several large-scale energy and AI-related projects, such as U.K. National Centre for Energy Systems Integration (CESI), U.K. Offshore Robotics for Certification of Assets Hub (ORCA Hub), Community-Scale Energy Demand Reduction in India (CEDRI), and Responsive Energy Flexibility Demonstration Project in Orkney Islands (Reflex). He is also a Principal Investigator and an Academic Lead of the Knowledge Transfer Partnership (KTP) Project NCEWS (Network Constraints Early Warning Systems) with SP Energy Networks.



MERLINDA ANDONI (Member, IEEE) received the Diploma degree in electrical and computer engineering from the National Technical University of Athens (NTUA), Greece, in 2010, and the M.Sc. and Ph.D. degrees in renewable energy and distributed generation from Heriot-Watt University, Edinburgh, U.K., in 2015 and 2019, respectively.

Since 2017, she has been working as a Research Associate with the Smart Systems Group, Heriot-Watt University, supporting U.K.'s National Centre for Energy Systems Integration (CESI) Project. Her research interests include investigating the potential of multi-agent systems, game theory and blockchain technologies for decentralized energy networks, and microgrids.

Dr. Andoni is a member of the Technical Chamber of Greece. Her awards and honors include the Academic Award in the Young Professionals Green Energy Awards 2018 and the Best Student Paper Award in a workshop in the AAMAS 2016 Conference.



DAVID FLYNN (Member, IEEE) received the B.Eng. degree (Hons.) in electrical and electronic engineering, the M.Sc. degree (Hons.) in microsystems, and the Ph.D. degree in microscale magnetic components from Heriot-Watt University, Edinburgh, in 2002, 2003, and 2007, respectively. He is currently a Professor of smart systems at Heriot-Watt University. He is the Founder of the Smart Systems Group (SSG), Heriot-Watt University. He is the Associate Director of U.K.'s

National Centre for Energy Systems Integration. The research of the SSG involves multidisciplinary expertise across energy systems, sensors, data analysis, and cyber physical systems. He teaches smart system integration, electrical engineering, and energy systems. He is an Institute of Engineering and Technology (IET) Scholar as a recipient of IET Leslie H Paddle Prize. He is the Vice Chair of IET Scotland. He is an Associate Editor of IEEE ACCESS.

...