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Real-Time Control of Distributed Batteries with Blockchain-Enabled Market Export Commitments

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***Abstract*—Recent years have seen a surge of interest in distributed residential batteries for households with renewable generation. Yet, assuring battery assets are profitable for their owners requires a complex optimisation of the battery asset and additional revenue sources, such as novel ways to access wholesale energy markets. In this paper, we propose a framework in which wholesale market bids are placed on forward energy markets by an aggregator of distributed residential batteries that are controlled in real time by a novel Home Energy Management System (HEMS) control algorithm to meet the market commitments, while maximising local self-consumption. The proposed framework consists of three stages. In the first stage, an optimal day-ahead or intra-day scheduling of the aggregated storage assets is computed centrally. For the second stage, a bidding strategy is developed for wholesale energy markets. Finally, in the third stage, a novel HEMS real-time control algorithm based on a smart contract allows coordination of residential batteries to meet the market commitments and maximise self-consumption of local production. Using a case study provided by a large UK-based energy demonstrator, we apply the framework to an aggregator with 70 residential batteries. Experimental analysis is done using real per minute data for demand and production. Results indicate that the proposed approach increases the aggregator's revenues by 35% compared to a case without residential flexibility, and increases the self-consumption rate of the households by a factor of two. The robustness of the results to uncertainty, forecast errors and to communication latency is also demonstrated.**

***Index Terms*—Batteries, Blockchain, distributed generation, smart contract, smart grids.**

NOMENCLATURE

Symbols

$\mathcal{C}$	Battery nominal capacity (Wh)
E	Energy quantity during the time interval corresponding to the superscript
E_B^{max}	Maximum energy quantity that the considered battery can provide/consume during a given time interval
E_c^t	Agreed contractual export for the aggregator's fleet within time interval t
ε_{RE}	State variable representing $\text{sgn}(RE^{t,k})$
η_d	Discharging efficiency of the considered battery
η_c	Charging efficiency of the considered battery
N_s	Number of PMS cycles within two consecutive times t_j
π_e	Wholesale market export price
π_i	Retail market import price
P_{B^k}	Power of the battery of household k
RE	Remaining Energy export required, either by the whole fleet (^{A}) or by a household (^{k})
$\mathcal{S}$	Battery operation state indicator, 0 if the battery must match residual demand, 1 otherwise
s	Time between two consecutive real time actions of the PMS
t_j	Time steps for the MPC optimisation at a household battery level. Corresponds also to the time at which MPC optimisation are run
t_{sc}	Time at which coordination with the Smart Contract happens
t_s	Time interval for PMS operations ($\approx 200\mu$s)
w_e^k	Percentage of the whole fleet export energy requested to household k
w_i^k	Percentage of the whole fleet import energy requested to household k

Subscripts and Superscripts

A	Virtual aggregated battery considered in phase 1 and 2 of the proposed framework
B	Battery
C	Charge
D	Discharge
d	Demand of the fleet or household, depending on the superscript
e	Export
i	Import
k	k^{th} household
l	Time steps for the MPC optimisation at a household battery level. Corresponds to t_j
p	Production from the renewable generation asset
t	Quantity computed over market time interval t (30

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minutes in most European countries)

Abbreviations

FIT	Feed-in Tariff
DER	Distributed Energy Resources
DRBCF	Distributed Residential Batteries Control Framework
DSO	Distribution System Operator
HEMS	Home Energy Management System
MILP	Mixed Integer Linear Programming
MPC	Model Predictive Control
PAR	Peak to Average Ratio
PMS	Power Management System
PV	Photovoltaic
ROI	Return on Investment
RT	Real-Time
RTC	Real-Time Control
ReFLEX	Responsive Flexibility
SoC	State of Charge
ToU	Time of Use

I. Introduction

INTEGRATING more residential renewable energy production is seen as key to building lower-carbon and resilient energy systems in many countries [1]. A key technology that has emerged to achieve this are small-scale home batteries, typically suitable for deployment in an individual dwelling with rooftop solar PV (e.g. Tesla Powerwall, ABB Residential, AlphaEss), which have seen fast technological development. However, a key barrier for faster adoption of home batteries is their economic cost, which can be above £6000 [2]. Furthermore, home battery capacity is often under-utilised at the individual domestic consumer level, and for this reason they are not cost-effective [3]. For example, although small batteries can have a reasonable investment recovery (payback) period [4], currently commercialised residential battery systems used solely for self-consumption in Europe or in the US have an investment recovery period ranging from 15 to 20 years, which is economically unattractive for domestic consumers [5]–[8].

To address this, there has been a surge of interest in using residential batteries to generate *secondary revenue streams*, especially through participation in wholesale energy markets. This is the context of the Responsive Flexibility (ReFlex) project, the UK's largest Integrated Energy System demonstrator project [9] that aims to decarbonise the Orkney Islands by integrating distributed storage such as domestic batteries in the current energy ecosystem.

However, although residential battery assets can be integrated more readily than large-scale batteries (e.g. less network operator concerns with respect to asset tripping or grid codes [10], [11]), home batteries are typically too small to participate in such energy markets by themselves (in most countries, wholesale energy markets are not open to small assets of power capacity below 1 MW [12]). Hence, one solution to allow residential assets to participate in wholesale markets consists in using demand-side *aggregators*, and designing real-time control (RTC) algorithms for home batteries that allow them to be used for a multiple objective: first, at the individual consumer level, to maximise local energy self-consumption through arbitrage. Second, at the aggregator level, to ensure that the fleet of aggregated small-scale domestic batteries participate profitably in wholesale markets. Designing algorithms that can handle these - often conflicting - objectives in real time with many distributed assets that usually communicate at time intervals of 5 to 10 minutes is a challenging problem, that requires a multi-layered approach and control solution. In more detail, it requires the integration of a number of techniques: a wholesale energy market bidding strategy at the aggregator level to maximise the fleet's revenues from the market, and a real-time control solution for every battery of the fleet with efficient coordination despite non-continuous communication.

In this work, we propose an integrated solution for this problem, by providing: a method to determine what quantities of energy an aggregator of residential assets can bid in the wholesale energy markets, and a real-time control algorithm for all these distributed assets, taking into account real constraints such as communication latency, retail and wholesale markets constraints and forecast errors.

Although prior works have addressed extensively the topic of energy market participation for stand alone assets or commercial Virtual Power Plants, they have not covered the context of many projects such as ReFLEX [9] that require to coordinate residential assets to participate in wholesale energy markets while maximising local self-consumption to make them profitable. Furthermore, in prior works, real-time control of home batteries has mostly been studied in the context of a single objective of arbitrage whereas a few works also implemented a multi-objective solution including arbitrage and *frequency* market participation in the same time [13], [14]. However, the problem of real time control of a fleet of domestic assets to perform local arbitrage and participate in *energy* markets has not been addressed yet. Indeed, unlike frequency markets that require participating assets to follow the frequency signal, energy markets require coordination between residential assets that do not communicate continuously due to technical constraints [2]. Therefore, there is a need to formulate a new real-time control algorithm and bidding strategy to address these concerns.

In terms of prior work on battery control, this has attracted a lot of research attention recently. On the *applications side*, the role of batteries for power grid applications has first been either to provide grid services such as frequency [13], [14] or voltage [15] regulation. Other works aimed to optimise the revenues of a battery owner such as a prosumer through arbitrage [8], [16], [17]. Although small residential batteries with small power electronics can provide payback periods below 5 years [4], current residential batteries with capacities of 5 to 10 kWh and with power above 5 kW able to supply a whole dwelling have payback periods that can be longer than the 10 years of battery life time [6]–[8]. As a result, some research works proposed control algorithms that allow energy producers to bid in the wholesale energy market [17]–

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[20] in order to increase the potential revenues provided by the battery. However, they only considered large-sized stand-alone batteries located in a single location, which is not compatible with the case of small-scale home batteries that usually cannot participate in wholesale markets alone and cannot be considered as a single battery given their distributed locations, communication limitation, and different environments (local consumption and production). Finally, several works such as [17], [19], [21], [22] propose solutions for future local peer to peer markets with residential batteries, involving game theory aspects but they are not compatible with the use of batteries distributed over a larger regional or national grid to participate in current wholesale markets.

On the *technical side*, RTC for batteries has been implemented through Model Predictive Control (MPC) [23], [24], or through heuristic rules [17], [25], and can consider battery degradation [24], [26] or not. Although it is relevant to study batteries degradation depending on the use of the battery [4], it was shown that for grid applications with currently commercialised residential batteries, it is usually not more financially profitable to consider battery degradation in the battery control algorithm [5], [8], [27]. However, most RTC algorithms apply either to the case of self-consumption only, or to the procurement of grid services, for which the strategy mostly consists in following either the frequency, or a specific signal from the grid operator [13]–[15]. Furthermore, although distributed batteries coordination has been successfully implemented for grid services such as frequency regulation in [19] and [28], these works do not address energy markets applications and assume perfect continuous communication between assets, which does not reflect real-life implementations with residential batteries. Hence, there is a clear and well defined gap in the literature to address the problem of the participation of distributed residential batteries in wholesale energy markets.

To address this challenge, we propose a framework to control distributed residential batteries that are aggregated into a fleet and coordinated by an aggregator to participate in wholesale energy markets. To achieve this coordination, we propose a blockchain technology based solution, that does not rely on a single authority or point of failure [29], [30]. We demonstrate that this framework benefits both the aggregator and the households hosting batteries by increasing their revenues. Therefore, our work provides a techno-economic and social-economic solution to incentivise investment into domestic renewable generation and local storage.

The key novel features of our framework include:

- A solution to aggregate distributed residential assets such as rooftop PV and domestic batteries to participate in wholesale energy markets under a real environment, which includes real constraints such as forecast errors, communication latency, and diversity of sizes and environment such as weather among assets. This solution includes the energy quantities and associated times that the aggregator can bid in the wholesale energy market.
- A real time battery control algorithm based on Model Predictive Control (MPC) and embedded in each Home Energy Management System (HEMS), that includes several objectives, such as local bill reduction, self-consumption maximisation, and commitment to the wholesale energy market bid from the aggregator.
- A comprehensive techno-economic study that demonstrates the economic interest for prosumers and aggregators to install residential generation assets at end-user premises while participating to wholesale energy markets. This study is based on wholesale energy market prices, real end-user pricing scheme and national grid imbalance prices to provide a comprehensive demonstration that the proposed framework is a viable solution to successfully deploy distributed assets at end-users premises. We also demonstrate the robustness of the proposed solution to different sources of uncertainty and communication latency.

In addition to these features, our framework is ”Blockchain-ready” as we implemented a blockchain-enabled smart contracting platform to coordinate the individual households exports. Such a blockchain platform also facilitates the settlement phase to distribute the aggregator’s revenues to each households.

The remainder of the paper is structured as follows. Section II presents a detailed overview of the proposed framework, while Section III describes the RTC algorithm for distributed batteries. Section IV presents the implementation and benefits in the case of 70 residential batteries participating in the day-ahead energy market, while Section V concludes with a discussion.

II. Distributed Residential Batteries Control Framework

In this section, we present an overview of our Distributed Residential Batteries Control Framework (DRBCF). It is designed to control a fleet of distributed residential batteries that make a joint energy export commitment on the wholesale energy market. These distributed batteries operated by an aggregator can either be owned by the aggregator or by the households. Hence, the use case of this study corresponds to the concept of ”Energy as a Service” in which an energy supplier or aggregator would manage distributed storage assets installed at end-user premises (residential households or commercial buildings) to provide cheaper and cleaner energy to the consumers. Therefore, the economic objective for prosumers is to reduce their bill, whereas the supplier or aggregator aim to maximise their revenues that come partly from a share of end-user energy bill reduction and from the wholesale energy market revenues. A secondary objective is to increase the share of renewable generation in end-users’ energy consumption mix.

A visual representation of the use case is shown in Fig. 1, corresponding to the real-life case study from the ReFLEX project [9]. As shown on the left side of Fig. 1, assets consist in residential or commercial buildings (load), generation from rooftop solar PV (Photovoltaic) or wind turbines, and also residential batteries installed at the end-user premises. The aggregator can also include his own assets in the portfolio (such as large PV or wind generation located in a single location). The DRBCF framework enables the aggregator to

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take advantage of these heterogeneous assets to bid energy quantities on the wholesale energy market, from which it generates revenues.

We note that market price formation and computation of bidding prices is not covered in this study – the aggregator is assumed to be a *price taker*. This is because, for a large-scale (national or regional) wholesale energy market, the ability of a small domestic aggregator to influence clearing prices is limited. Also, as presented in Section III, at the time of delivery, a dedicated smart contract and a RTC algorithm embedded in every household HEMS ensure that the distributed batteries will meet the commitments made on the markets.

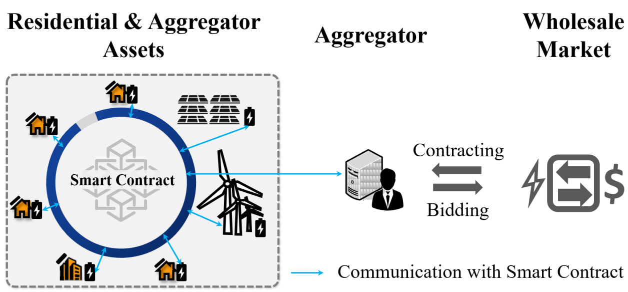

Fig. 1: Use case representation: an aggregator manages distributed assets at households and building premises, but also a wind farm and a solar PV farm.

The control framework DRBCF can be divided into three main phases as detailed in Fig. 2. In the first phase, based

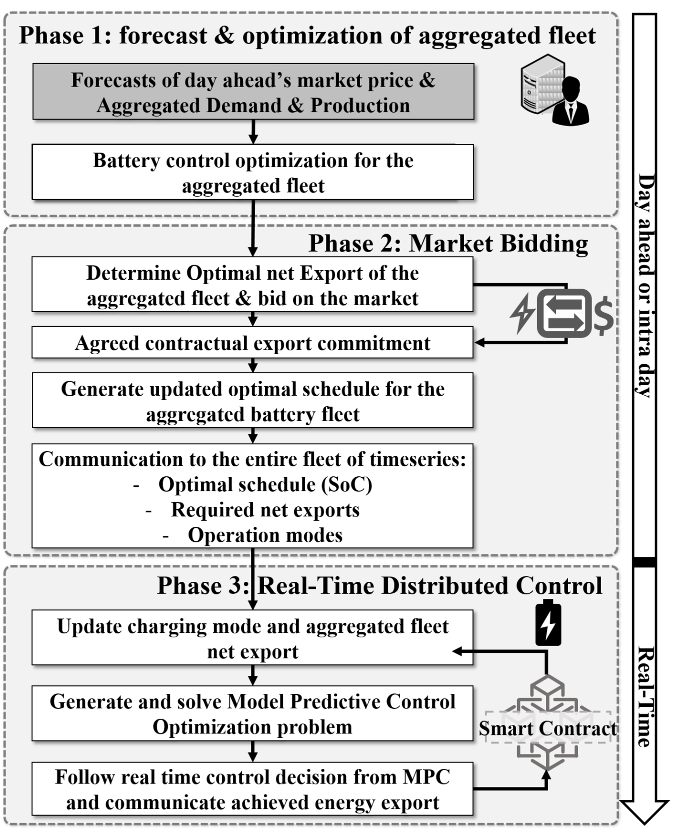

Fig. 2: DRBCF Framework for the control of distributed residential batteries contributing to the wholesale market.

on forecasts of wholesale market prices, aggregated demand of residential loads and production of the whole fleet, the aggregator solves (1) to compute $E^t_{e^A}$, a first estimation of the optimal market bidding quantities and associated time. For this computation, the aggregator considers a virtual fleet as if all assets were not distributed but aggregated into one large virtual load, one large virtual PV and wind generation site, and one large virtual battery. The optimisation problem (1) is a Mixed Integer Linear Programming (MILP) formulation that is detailed in [5], where each time interval t corresponds to the wholesale market intervals (30 minutes in European countries, including the UK), and the time horizon can be a day:

$$\begin{aligned} \underset{E^t_{B^A_D}, E^t_{B^A_C}, \forall t}{\text{minimize}} \quad & \sum_{t=1}^{T} \left(E^t_{i^A}\pi^t_i - E^t_{e^A}\pi^t_e \right) \\ \text{subject to} \quad & (2),\ (4),\ E^t_{B^A_D}, E^t_{B^A_C}, E^t_{i^A}, E^t_{e^A} \ \geq 0, \\ & E^t_{B^A_D}, E^t_{B^A_C} \leq E^{max}_{B^A},\ \forall t, \end{aligned} \tag{1}$$

where $E^t_{B^A_D}, E^t_{B^A_C}$ are the discharged and charged energies of the aggregated battery capacity in time interval t respectively, $E^t_{i^A}$ and $E^t_{e^A}$ are the optimal net import and export of the aggregated fleet of assets (residential loads, production and batteries) in time interval t, and $E^{max}_{B^A}$ is the maximum energy the virtual aggregated battery can import or export during the considered time interval. It corresponds to a limit in maximum power, which is computed as the sum of the powers of all the storage assets that constitute the aggregator's fleet. Superscript A refers to aggregated quantities. Indeed, in phase 1 and 2 of the DRBCF, the aggregator considers all distributed assets and loads as if they were only one asset. Differentiation between assets being done in Phase 3. π^t_i is the retail price of electricity (import from the grid) and π^t_e is the forecasted wholesale market price for time interval t. Constraint equation (2) corresponds to the energy balance:

$$\begin{aligned} E^t_{i^A} + \eta^A_d E^t_{B^A_D} - \frac{E^t_{B^A_C}}{\eta^A_c} &= E^t_{d^A} - E^t_{p^A} \\ E^t_{e^A} - \eta^A_d E^t_{B^A_D} + \frac{E^t_{B^A_C}}{\eta^A_c} &= E^t_{p^A} - E^t_{d^A} \end{aligned} \tag{2}$$

where η^A_d and η^A_c are the discharging and charging efficiencies of the virtually aggregated battery respectively given by (3), and $E^t_{d^A}$ and $E^t_{p^A}$ are the forecasted energy demand and production respectively of the whole portfolio of the aggregator (end-users' loads and generation assets such as PV and wind).

$$\eta^A_{d,c} = \frac{\sum_{k \in households} \mathcal{C}_k \eta^k_{d,c}}{\sum_{k \in households} \mathcal{C}_k} \tag{3}$$

where $\eta^k_{d,c}$ is the efficiency of the battery of household k, and $\mathcal{C}_k$ is its nominal capacity. Then, (4) expresses the state of charge (SoC) limits for the virtually aggregated battery capacity and also applies to every time interval t.

$$SoC^A_{min} \leq \sum_{l=1}^{t} \left(E^l_{B^A_C} - E^l_{B^A_D} \right) + SoC^{0,A} \leq SoC^A_{max}, \tag{4}$$

where superscript 0 corresponds to the quantities at the start of the considered period, for $t = 0$. $SoC^A_{max} = \mathcal{C}_A$ is the maximum available capacity of the virtually aggregated battery, and corresponds to the sum of the capacities ($\mathcal{C}_k$) of all the storage assets that constitute the aggregator's fleet. Forecasts are inputs of the model that are not in the scope of this paper, but can be generated using statistical or AI methods such as Artificial Neural Networks or K-Nearest Neighbour regressions with good accuracy when considering aggregated assets, which is the case in phase 1 and 2 [31].

In phase 2, the aggregator uses the energy export quantity $E^t_{e^A}$, output of the optimisation problem (1), to determine the optimal energy quantities to bid on the wholesale energy market. Once the wholesale energy market is cleared, the aggregator receives a pre-agreed energy schedule, E^t_c for all t. If this schedule differs from the submitted bids, the aggregator will re-run the optimisation of the virtual aggregated battery given in (1) based on an updated *price* time-series such that $\pi^t_e = 0$ for all the time intervals t without export contract. Similarly, constraints for the net exported energy $E^t_{e^A}$ must be updated such that $E^t_{e^A} = E^t_c$ when an export contract was awarded, with E^t_c the agreed contractual export in MWh for time interval t. The second phase is completed once the aggregator circulates the following time series to the distributed fleet: (i) the optimised SoC profile for the virtual aggregated battery capacity $SoC^{t,A}$ in % for every time-step of the considered period (day ahead e.g.), (ii) the required aggregated net export quantities E^t_c for every coming market periods, and (iii) a *state indicator*, $\mathcal{S}$, that represents the mode of operation of the aggregated battery capacity for every time interval:

$$\mathcal{S} = \begin{cases} 0 & \text{if Battery power must match residual demand} \\ 1 & \text{otherwise.} \end{cases} \tag{5}$$

where the residual demand consists of the difference between the demand and production of the considered system.

The third phase of the framework corresponds to the RT operation of the distributed batteries as detailed in section III. Coordination among all residential batteries is achieved through a smart contract that ensures that the whole fleet will export energy quantities E^t_c agreed on the wholesale market.

III. Real-Time Control of Distributed Batteries

Unlike prior research that considers large batteries for wholesale energy market applications, distributed residential batteries must have a dedicated control algorithm to maximise local self-consumption, while helping the fleet to meet the wholesale market commitments. This section introduces our novel algorithm that optimises local self-consumption while ensuring coordination and energy sharing between assets.

A. Model-Predictive Control Algorithm

In this paper, RT control consists of power set-points computed by every household's HEMS and sent to the household's battery at every time step of its operation cycles (from μs to ms). This RTC of each household's battery is achieved through an approach inspired from Model Predictive Control (MPC) where the system that is modelled corresponds to the household's demand and production forecasts and the storage asset. At every time intervals t_j (e.g. $t_{j+1} - t_j = 1$ or 2 min), each HEMS solves a local optimisation problem specified in (6) where the time horizon t corresponds to the rest of the considered market time interval. The output of (6) is a series of set-points ($E^{t_{j+1}}_{B^k_{C,D}}, E^{t_{j+2}}_{B^k_{C,D}}, ...E^{t}_{B^k_{C,D}}$) from which the HEMS will keep the first one, $E^{t_{j+1}}_{B^k_{C,D}}$, that will be sent as a set-point to the Battery Power Management System (PMS) of the household's battery. Unlike previous implementations of MPC for battery control that consider either a single objective of bill reduction or self-consumption [23], [24], or that aim to regulate the grid through balancing frequency or voltage [32], [33], the proposed algorithm includes two objectives, i.e. the maximisation of self-consumption at the household level, but also the integration of the market commitments, which can imply the need for charging or to empty the battery at a given time. These two objectives being sometimes contradictory, it is necessary to arbitrate them. This arbitrage is achieved through variables ε_{RE} and $\mathcal{S}^t$ described below. Furthermore, this second objective also depends on the actions taken by the rest of the fleet of residential assets, which requires a different approach than the one other works propose for single stand alone batteries. The MPC formulation given in (6) corresponds to a novel solution to these challenges.

Since the time horizon t of the optimisation problem can be up to 30minutes ($t - t_j$), the MPC optimisation problem computes the optimal battery schedule ($E^{t_{j+1}}_{B^k_{C,D}}, E^{t_{j+2}}_{B^k_{C,D}}, ...E^{t}_{B^k_{C,D}}$) with relatively large time steps equal to $t_{j+1} - t_j \approx 1$min, so the computation of (6) can be tractable. Hence, it does not correspond to a RT schedule as RT time steps for a battery control (noted t_s in this paper) are usually in the order of the μs or ms. Therefore, between two consecutive optimisations that occur at times t_j and t_{j+1}, the Battery PMS will take N_s operational decisions (charging/discharging) that correspond to the recommendation from the first step of the optimal schedule ($E^{t_{j+1}}_{B^k_{C,D}}$), where N_s is the number of RT operations/cycles between t_j and t_{j+1} ($t_{j+1} - t_j = N_s t_s$), and depends on the clock frequency of the PMS. The recommendation can either be to compensate or follow the local residual demand, such that there is no energy export nor import in the period, or to apply a specific charge/discharge power given by $E^{t_{j+1}}_{B^k_{C,D}}$, which is the first step of the optimal schedule. Finally, it should be noted that battery degradation, which was added in our previous work in [5], is not added here as it was shown that the impact on battery life time is limited [5], [8], [27].

Fig. 3 details the chronology of the MPC algorithm. There are 4 time indicators to be considered.

- t, the current market time interval, corresponds to the time horizon for the MPC optimisation (for example $t - (t_{-1}) = 30$min).
- t_{sc} is the time at which each HEMS sends and receives the last information to/from the smart contract (vertical arrows in grey in Fig. 3), for coordination with the rest of the fleet (for example $t_{sc} - t_{sc-1} = 5$min).

$$\begin{aligned}
\underset{E^l_{B^k_D}, E^l_{B^k_C}, \forall l}{\text{minimize}} \quad & \sum_{l=t_{j+1}}^{t} E^l_{i^k}\pi^l_i + (1-\varepsilon_{RE})E^l_{e^k}\pi^l_e + \mathcal{S}^t(1-\varepsilon^2_{RE})\frac{SoC^{t,A}-SoC^{t,k}}{SoC^k_{max}} + \varepsilon_{RE}\frac{\left|RE^{t,k} - \sum\limits_{l=t_{j+1}}^{t}\left(E^l_{e^k}-E^l_{i^k}\right)\right|}{\max(E^{max}_i, E^{max}_e)} \\
\text{subject to} \quad & (2),\ (4),\ E^l_{B^k_D}, E^l_{B^k_C}, E^l_{i^k}, E^l_{e^k} \ \geq 0,\ E^l_{B^k_D}, E^l_{B^k_C} \leq E^{max}_B,\ \left(E^l_{i^k}-E^l_{e^k}\right) \geq E^{max}_i, \left(E^l_{e^k}-E^l_{i^k}\right) \leq E^{max}_e,\ \forall l.
\end{aligned} \tag{6}$$

- t_j is the time at which MPC optimisations are executed (e.g. every 2 minutes).
- Finally, the smallest time step t_s (vertical markers in grey in Fig. 3) corresponds to the cycle time for the battery PMS RT operations (e.g. $t_s - t_{s-1} = 200\mu$s).

At the beginning of each market time interval t, the HEMS initializes $RE^{t,A}$ (the remaining net export required from the whole fleet) with the value that was communicated originally by the aggregator at the end of the phase 2 in Fig. 2. At every communication time with the smart contract t_{sc}, each HEMS receives an updated value of $RE^{t,A}$ that can be negative if the fleet produced more than what was committed to the wholesale market. Along with $RE^{t,A}$, the smart contract communicates 2 weights values w^k_e and w^k_i to each household k, that represent the percentage of $RE^{t,A}$ that should be exported (w^k_e if $RE^{t,A} > 0$) or imported (w^k_i if $RE^{t,A} < 0$) by the household k for the rest of time interval t. The details of the weights computation are provided in the next subsection. With these information, each HEMS updates $RE^{t,k}$, the remaining net export required from the household k before the end of the market interval:

$$RE^{t,k} = \begin{cases} RE^{t,A}\cdot w^k_e - \sum\limits_{l=t_{sc}}^{t_j}\left(E^l_{e^k}-E^l_{i^k}\right), & \text{if } RE^{t,A} \geq 0 \\ RE^{t,A}\cdot w^k_i - \sum\limits_{l=t_{sc}}^{t_j}\left(E^l_{e^k}-E^l_{i^k}\right), & \text{otherwise,} \end{cases} \tag{7}$$

where $\sum_{l=t_{sc}}^{t_j}\left(E^l_{e^k}-E^l_{i^k}\right)$ corresponds to the effort (export or import) that was already realized by the household k since t_{sc}, the time of the last communication with the smart contract.

The HEMS also computes a forecast of the household's future consumption and production for the remainder of the current market interval. In our simulations, the HEMS generates a forecast for the next 30 minutes with 15 minutes time steps, using a Linear Regression model, as it was shown to be the best compromise between speed and accuracy for forecasts of up to 1 hour ahead. Beyond this forecasting horizon, K-Nearest Neighbour regressions showed better accuracy results.

As it is shown in (6), the whole MPC optimisation problem formulation includes the cost of electricity imports at the prosumer level, but also a penalty for energy exports when there is no export contract with the wholesale market, in order to incentivise self-consumption. It also includes the SoC recommendation $SoC^{t,A}$ and net export requirements $RE^{t,k}$ that have been coerced into achievable values. ε_{RE} is a state variable such that $\varepsilon_{RE} = \text{sgn}(RE^{t,k})$, and $\mathcal{S}^t$ is the battery state indicator for time interval t sent by the aggregator (5). $SoC^{t,k}$ is the state of charge of battery k at the end of the time interval t. $RE^{t,k}$ is updated before each MPC optimisation using (7). Finally, $\left(E^l_{e^k}-E^l_{i^k}\right)$ is the net export from household k at time l, and is determined by (2), where t must be replaced by l, and superscript A replaced by k, noting that l corresponds to the optimisation time intervals (t_j), e.g. 2 minutes between two consecutive times l. Then, variables E^{max}_i and E^{max}_e introduced in (6) correspond respectively to the maximum imported and exported energy quantities allowed over a time interval $t_j \approx$ 2min. This represents a limit in imported/exported power that can be set as functions of the local voltage or grid frequency, following recommendations from the grid operators. For example, in a situation where the frequency rises above 50.2Hz in the UK, then E^{max}_e could be set equal to 0Wh for all households. Similarly, if the voltage rises above 230V +10% in a given location, E^{max}_e could be set equal to 0Wh for households located in this area.

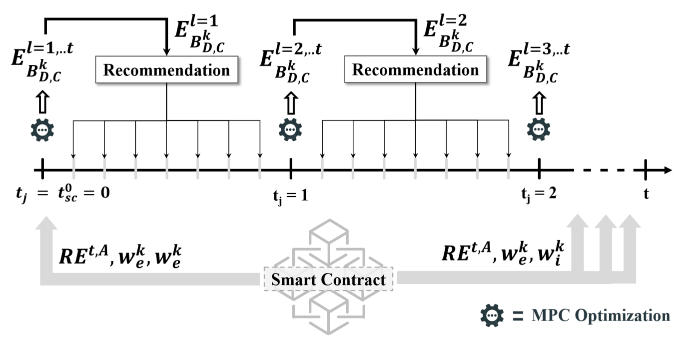

Fig. 3: MPC process with smart contract communication.

Finally, introducing a positive auxiliary variable $x \geq \left|RE^{t,k} - \sum\limits_{l=t_{j+1}}^{t}\left(E^l_{e^k}-E^l_{i^k}\right)\right|$, converts (6) into a MILP optimisation problem. The solution of the optimisation consists in the optimal battery schedule given by $E^{l=t_{j+1},\dots,t}_{B^k_{C,D}}$, from which the first charging and discharging energy quantities $E^{l=t_{j+1}}_{B^k_{C,D}}$ are sent to the battery's PMS as set-points for the battery power $P^s_{B^k}$, to be followed at every time step t_s of the PMS operation between t_j and t_{j+1}. $P^s_{B^k}$ is the power of the battery system, and is positive (negative) when the battery is charging (discharging):

$$P^s_{B^k} = \begin{cases} \eta \left[P^{t_s}_{p^k} - P^{t_s}_{d^k} \right], & \text{if } E^{t_{j+1}}_{B^k_C} - E^{t_{j+1}}_{B^k_D} = \eta \left[E^{t_{j+1}}_{p^k} - E^{t_{j+1}}_{d^k} \right] \\ \frac{E^{t_{j+1}}_{B^k_C} - E^{t_{j+1}}_{B^k_D}}{s \cdot N_s}, & \text{otherwise,} \end{cases} \tag{8}$$

where s is the time between two consecutive RT actions ($s = t_s - t_{s-1}$), and η is given by:

$$\eta = \begin{cases} \eta_c, & \text{if } P^{t_s}_{P^k} - P^{t_s}_{D^k} \geq 0 \\ \dfrac{1}{\eta_d}, & \text{otherwise.} \end{cases} \tag{9}$$

This real-time control algorithm presented in this subsection is implemented in the Home Energy Management System of each participating household. As it was mentioned, it requires a certain level of coordination with the rest of the fleet to ensure market commitments (through $RE^{t,A}, w^k_e$, and w^k_i). This coordination can either be done using a centralised approach, where coordination is achieved through direct communication between the assets and the aggregator's server, or it can be distributed using distributed ledger technologies. The next subsection explains how blockchain technologies can be used to achieve such coordination, although the centralised approach can be used indifferently by implementing the following equations in a central server.

B. Smart Contract Platform

A blockchain-enabled smart contract between the aggregator and the fleet of distributed batteries coordinates each battery operation and ensures that contractual export commitments E^t_c to the wholesale market are met. It also coordinates the sharing of energy surpluses within the fleet and allows an automatic redistribution of the aggregator's benefits among the participants. The smart contract represents a distributed and tamper-proof way that increases the reliability and security of the coordination of the battery fleet, by removing a single point of failure and by improving resilience to cyber-attacks. This is in comparison to a centralized operation realised by a single server. Indeed, in the proposed Smart Contract approach, distributed nodes, computers or HEMS aggregate to create a virtual environment that will execute the contract each time it is needed. This increases the reliability as the number and geographical distribution of nodes limit the risk of a global failure of the virtual environment compared to the case of a single server implementing the coordination scheme. Furthermore, the smart contract allows for automatic self-verification of commitments and exports of the fleet of batteries, thereby not relying on a single aggregator authority. Furthermore, such Smart Contract implementation is especially relevant for the aggregation of distributed residential assets as it makes the settlement phase easier, more transparent and automatic for all the agents. Indeed, based on the measurements sent by each HEMS or smart meter, the smart contract automatically distributes the benefits from the aggregator to the households based on their recorded exports. Finally, although smart contracts are not well adapted to full RTC with milliseconds time interval communication, the proposed algorithm relies on minutely to 15 minutes time intervals' communication between the assets and the smart contract, making it suitable for smart contract implementation on a permissioned blockchain.

In our experiment, the smart contract was implemented in an Ethereum-based private blockchain using the Ganache environment. It was developed using Solidity, and compiled and deployed using Python's library web3.py [34]. Each HEMS was associated with an account, similar to the aggregator, who deploys and manages the smart contract and associated operating fees, as shown in Fig. 4.

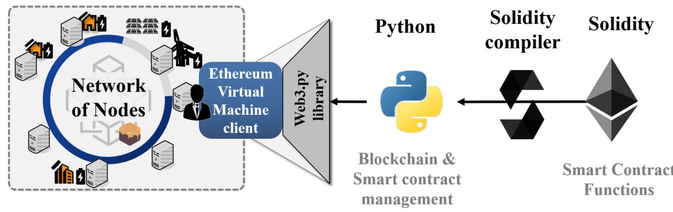

Fig. 4: Local smart contract implementation for distributed batteries coordination. The deployment and management of the smart contract is detailed for the aggregator node.

The functions implemented in the smart contract are listed below:

- Constructor, to initialize the contract.
- Register a new household.
- Update the time series sent by the aggregator ($SoC^{t,A}, E^t_c, \mathcal{S}^t$).
- Update a household information: $SoC^{t_{sc},k}$ the battery SoC at the current time, $E^{t_{sc},k}_e$ the energy exported/imported by household k since the last communication between the battery k and the smart contract, and $E^{t,k}_e$ a new variable equal to the net exported energy of household k since the beginning of time interval t. It is computed as the sum of all previous quantities $E^{t_{sc},k}_e$.
- Compute the batteries weights w^k_i and w^k_e for all the batteries k. The weights are computed as follows:

$$w^k_e = \frac{W^k_e}{\sum\limits_{k \in households} W^k_e}, \quad w^k_i = \frac{W^k_i}{\sum\limits_{k \in households} W^k_i} \tag{10}$$

  where $W^k_i = 100\% - SoC^{t_{sc},k}$ and W^k_e is given by:

$$W^k_e = \begin{cases} SoC^{t_{sc},k} & \text{if } E^{t_{sc},k}_e \geq 0 \ , \ SoC^{t_{sc},k} \geq SoC^{t,A} \\ 0 & \text{Otherwise.} \end{cases} \tag{11}$$

- Compute $RE^{t,A}$ the remaining aggregated energy to be exported:

$$RE^{t,A} = E^t_c - \sum_{k \in \text{households}} E^{t,k}_e. \tag{12}$$

- Provide the required information to all registered households using the emit method: $RE^{t,A}, w^k_e, w^k_i$.

The cost of this smart contract for a portfolio of 70 batteries is around 105957 gas units when implemented on an Ethereum blockchain, which corresponds to 0.002 ether or 0.7$, to be paid at every time step $t_{sc} \approx 15$min. However, this cost can be

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reduced to only the nodes operation costs if the smart contract is realised on a permissioned blockchain.

IV. Experimental validation

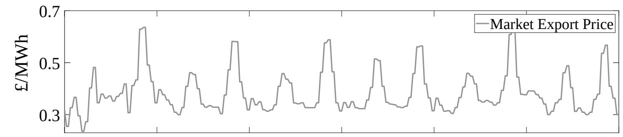
A. Experimental set-up and case study

The proposed DRBCF framework was implemented for the use case described in section II, that reflects the settings of our large-scale demonstrator [9]. An aggregator invests in distributed residential batteries and generation assets (rooftop PV) and installs those at customers' premises. 70 households were considered in this study, each of them with a micro-generation asset and a residential battery [2]. Households are incentivised to participate in such scheme by a reduction of their electricity bill, and by the reduction of CO_2 emissions associated with their energy consumption. Such incentives in the ReFLEX project were sufficient for households in the UK to allow the aggregator to control the battery to achieve these two objectives. To address a more general case, the aggregator also owns large generating assets that include one PV power plant of 105 kW and one wind farm of 130 kW. Although these two large-scale assets are not predictable and could have led to over or under delivery without our proposed framework, it will be shown in this section that the algorithm described in Section III takes advantage of all distributed batteries to counterbalance potential forecast errors, and ensure that the commitments on the wholesale energy market will be met. The data used for the demand and production profiles are

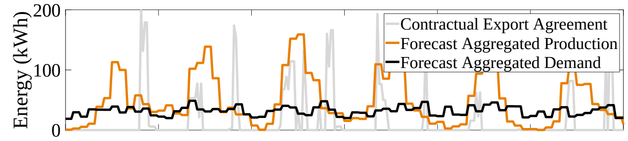
TABLE I: Breakdown of an electricity bill [35].

Bill component definition	Value (%)
Wholesale costs	32
Supplier Operation costs	17
Supplier margin	1
Supplier direct costs	2
Network costs	23
Environmental & social obligation costs	20
VAT	5

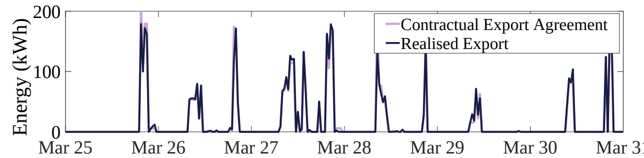
minutely data from real measurements from the ReFLEX project [9]. The pricing data for the wholesale market price have been extracted from Nordpool's day-ahead market for the UK [36]. Retail import prices follow dynamic Time of Use (ToU) pricing scheme from [37]. Market time interval is 30 minutes. We do not consider export tariff for households (such as FiT), as these incentives are either being removed or very small (e.g. 2p in the UK). Furthermore, as forecasts errors and communication latency can lead RT operations to achieve different export energy quantities than the contractual agreement, we considered wholesale market penalties that can apply to the aggregator, equal to the product of the energy quantity difference and an imbalance price. Imbalance prices were taken from [38]. Also, we consider that the fleet is linked by a virtual private wire contract [39], which means that when a household consumes electricity that is produced by another asset of the fleet, the electricity price paid by the consumer is equal to 48% of the retail import price. This corresponds to the network costs with environmental and social taxes and neglects the production costs and supplier fees, as shown in Table I [35]. This percentage is currently fixed irrespective of the distance between the producer and the consumer [35].



(a) Norpool day-ahead wholesale market

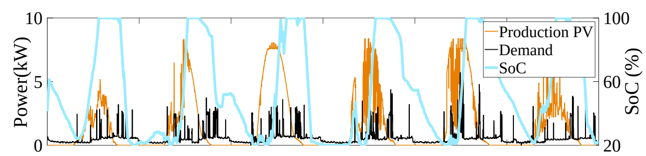


(b) Aggregated Forecasts and Contractual agreements

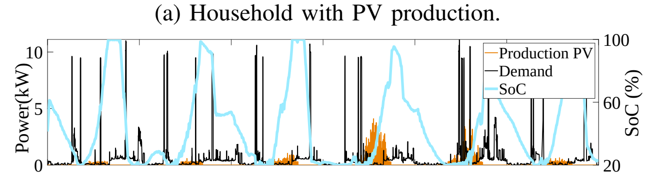


(c) Realised export from the whole fleet

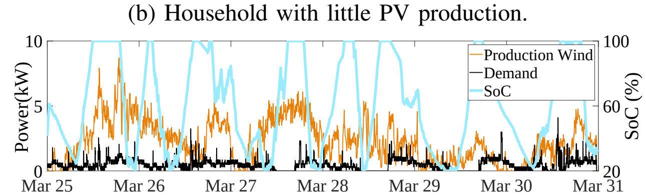
Fig. 5: Experimental results with 30 minutes time intervals



(a) Household with PV production.



(b) Household with little PV production.



(c) Household with micro-wind generation.

Fig. 6: Production, demand and resulting SoC for different households with time intervals of 1 minute.

B. Experimental Results

The results presented in this section were obtained with a communication time interval of 5 minutes between the assets and the smart contract. Similarly, day-ahead forecasts from Phases 1 and 2 were voluntarily worsen to achieve an error of 25%, with a time interval of 2 hours between two forecast points, which is conservative as forecasts are done for the virtually aggregated whole fleet, for which forecast accuracy is more reliable than for individual assets.

Fig. 5.a shows the wholesale market price. Fig. 5.b displays the aggregated demand and production forecasts, along with the fleet net energy export from (1) contracted in the wholesale market. Finally, Fig. 5.c compares this contractual energy export quantities with the realised export of the aggregated fleet after RT operations. The realised export match the market commitments with an average error below 10%. Fig. 6 shows the real consumption and production data for three different households, along with their battery SoC that results from the RTC operations. It shows that the SoC is following the local demand and production as the SoC of the household with wind generation (Fig. 6.c) is different than the SoC of batteries in households owning solar PV generation. This demonstrates one of the novelty aspect of the proposed algorithm: although residential batteries are coordinated at a pace of 5 minutes to meet markets commitment, local RT control provided by each HEMS maximises each household's own self-consumption.

We will now assess the economic benefits that an aggregator can expect from the proposed DRBCF framework. The source of revenues for the fleet is the revenues from energy exports agreed on the wholesale energy market and the total bill reduction of the households due to their self-consumption. The bill reduction is computed as the total bill difference between the baseline scenario without distributed generation (Scenario 0 defined below without battery and rooftop PV) and the total bill after the framework is implemented (scenario 4). Based on the ReFLEX demonstrator project, a number of scenarios have been considered for comparison purpose:

Scenario 0 (baseline) considers the 70 households' demand only, and assumes they do not have any distributed generation asset (no rooftop PV nor batteries).

Scenario 1 considers the households individually, with a rooftop PV and a residential battery, but without any aggregator and without any revenue from energy exports to the grid. The batteries are individually controlled using an heuristic based RT control algorithm [5], [27] that provides similar revenues as an optimisation-based algorithm when batteries do not export to the grid [5].

Scenario 2 considers an aggregator that would install all the residential generation assets in the same location, resulting in a large scale PV power-plant and battery, controlled by the proposed RT algorithm considering only one asset ($k = 1$). Therefore, households' demand is not included in the aggregator's portfolio for this scenario, and the aggregator sells all the energy in the wholesale market.

Scenario 3 corresponds to Scenario 2 (centralized generation assets) with the addition of distributed individual households in the aggregator's portfolio, and no distributed assets as they are kept installed in a single location, as for Scenario 2. The aggregator bids on the energy market, and proposes a specific retail contract to the individual households, using a virtual private wire contract, but no assets are installed at the end-users premises. Hence, when households consume electricity, they pay either the ToU tariff or a reduced tariff (48% of the ToU tariff [35]) when centralised generation assets export.

Scenario 4 considers distributed residential assets with an aggregator that bids on the wholesale energy market. It corresponds to the main use case of this paper where each households has a micro-generation asset and a residential battery controlled by the RTC algorithm described in Section III.

Scenario 5 corresponds to the Scenario 1, but without any battery. It is used only for comparison purpose in the next section to assess the impact of Scenario 4 on the grid.

Table II displays the monthly bill reduction compared to the baseline (scenario 0) in each scenario, along with the monthly revenues from the market exports. The last column displays the total revenue for the fleet, computed as the sum of the bill reduction and market revenues. The installation costs for solar PV and batteries were extracted from [40].

TABLE II: Comparison of economic benefits on a monthly basis of the proposed RT control framework

Scenario	**Energy Bill Reduction (£)**	**Market Revenue (£)**	**Total Revenue (£)**	**ROI (years)**
0	0	0	**0**	-
1	2032	0	**2032**	17
2	0	2722	**2722**	13
3	2620	818	**3438**	10
4	2887	802	**3689**	9
5	1014	0	**1014**	12

Table II shows that the proposed RTC algorithm for distributed batteries in Scenario 4 provides £3689 of monthly revenue to the community, which is the greatest revenues among all the scenarios, and consequently the shortest time of return on investment (ROI). Indeed, the ROI using the proposed framework (scenario 4) is almost half the one of scenario 1, which is the current state of the art scenario for residential batteries used for self-consumption or arbitrage purpose. It demonstrates that it is more profitable for prosumers to allow an aggregator to control their battery assets to generate extra revenue, as long as RT local control maximises self-consumption as it is proposed in our algorithm.

Furthermore, comparing the results of scenario 4 with other scenarios involving an aggregator (Scenarios 2 and 3), we can see that bidding on the market while taking advantage of distributed residential generation for self-consumption allows an aggregator to increase its revenues by 35% compared to Scenario 2 in which an aggregator does not include households demand in his portfolio. However, including household demand in a portfolio will not provide the greatest revenues, it is also important to install generation assets at the location of demand and maximise self-consumption while ensuring market commitment are met. Indeed, the proposed framework increases the revenues by 7% compared to Scenario 3, in which an aggregator includes households demand in his portfolio and invests in generation assets (PV and batteries) installed all at a single location. Although this result may seem counter intuitive, it is due to the fact that in the case of centralized generation assets with distributed residential loads (Scenario 3), electricity imports from households always include a network cost (48 % of the import tariff) that does

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not apply in Scenario 4 when households consume their own production.

Given the conservative choices for forecast uncertainty and communication latency in Scenario 4, the performance of the proposed RTC algorithm is demonstrated. This performance is explained by the fact that the proposed algorithm leverages the advantages of residential self-consumption (bill reduction by self-consumption) and the advantages of wholesale market participation. This shows that it can be profitable for investors to support self-consumption by investing in decentralized generation assets with market bidding. Finally, along with the financial gain of using the proposed framework, this study also demonstrates that the proposed scheme increases the self-consumption rate for end-users: indeed, the average amount of time households are self-supplied by their generation assets has increased from 28% of the time in the scenario with only micro-generation (Scenario 5) to 64% of the time in scenario 4 with the proposed framework. Similarly, the self-consumption rate, defined as the ratio between the energy self-consumed by the households and their energy consumption, has been increased by 2, from 22% for Scenario 5 to 41% for Scenario 4, with the proposed scheme.

C. Sensitivity study of the RTC algorithm

In this subsection, we study the impact of forecast inaccuracy and communication latency on the total revenues.

1) Sensitivity to forecasts: two forecasts parameters have been considered: forecast accuracy and forecast time steps. Several simulations were run over a range of these two parameters and resulting revenues were averaged and displayed in Fig. 7. The forecast accuracy is the parameter that has the greatest impact on the revenue. However, the proposed RTC algorithm ensures that even with a minimum accuracy of 20%, the monthly revenues for the fleet stays above £2970, which makes the distribution of micro-generation assets more profitable than Scenario 2.

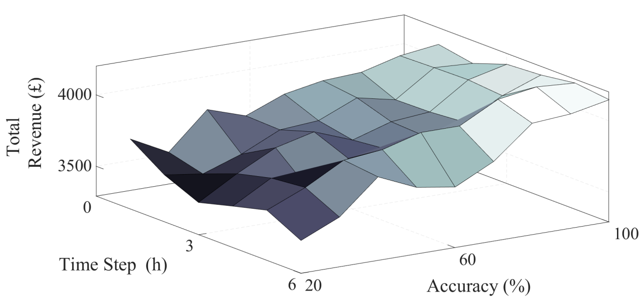


Fig. 7: Total monthly revenues of the fleet obtained for different forecast accuracies and forecast time steps.

2) Sensitivity to communication time interval: simulations were run with different communication time intervals between the assets and the smart contract, ranging from 1 minute to 15 minutes. The total revenues resulting from the RTC algorithm showed good robustness to communication latency as they ranged from £3798 for 1 min communication time interval to £3375 for 15 min, and therefore provided better revenues than all other scenarios for communication time intervals below 15 minutes.

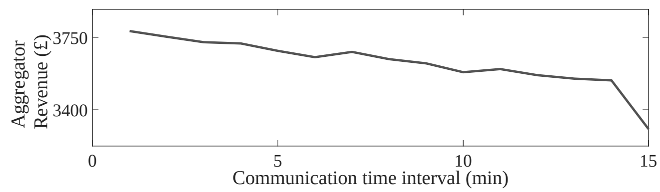
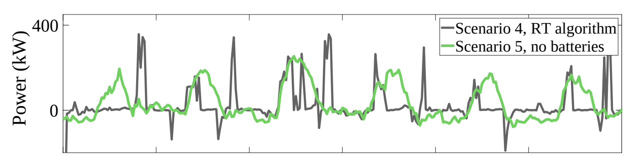


Fig. 8: Revenues of the aggregator obtained for different communication time intervals.

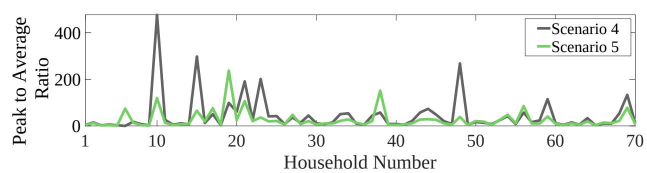
D. Impact for the grid

Finally, we study the impact of the proposed battery control on the electrical grid (which can be regional or national scale, in the UK case).

1) System level: Fig. 9.a shows the power profiles of the aggregated fleet for scenario 4 (in dark) and scenario 5 (in green) that corresponds to the DER installation scheme we experience nowadays, with only households with rooftop PV and no residential batteries nor aggregator. It shows that the profile of the aggregated fleet with batteries (Scenario 4) is relatively flat, except for periods when export is incentivized by the national grid. However, this should not impact the system operation (and especially the frequency regulation) as such large export happen at times where export was incentivized. However, in order to ensure the fleet does not endanger the grid, variables E_i^{max} and E_e^{max} in (6) that limit the exported and imported power can be set as functions of the grid's frequency. As the fleet is distributed over a large area (national grid in the UK), these peaks have a low impact on the voltage, as it will be discussed below.



(a) Net power profile of the aggregated fleet of assets.



(b) Peak to Average Ratio for all considered households.

Fig. 9: Impacts of Scenario 4 and 5 on the grid.

2) Local level: At a local level, we study how the proposed framework can affect the voltage and cables temperature. Fig. 9.b compares the Peak to Average Ratio (PAR) before and after the installation of the batteries for each household. The PAR for scenario 4 is comparable in magnitude with the PAR before batteries were installed. Indeed, although the PAR values for households 10, 15 and 48 has considerably increased, this is due to a reduction of the average power consumption by a factor 4, close to 0. As an example, Fig. 10 shows the load profile of an household with and without batteries. We can see the displacement of production in order to follow the price

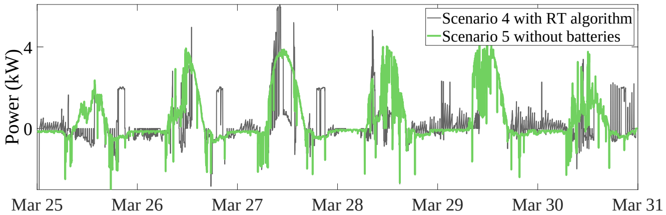


Fig. 10: Example of load profile comparison between scenario 4 and scenario 5 at a household level.

incentive from the wholesale market. It can be seen from the shape of the load profile that the situation will be the same as for the current situation with PV only: if many batteries participating to the same aggregator's fleet were located on the same primary transformer, the local voltage could be impacted and rise during a period of export commitment.

However, the maximum power exported to the grid can be constrained locally, as shown in (6) that includes a constraint on the maximal import and export powers allowed by the DSO or the fleet aggregator for the considered household. Therefore, this export power is limited so it does not impact the local grid. It is important to note that in a case where several households of the same area are not allowed to export, the coordination scheme will ensure the export commitment will be supported by the rest of the fleet. Hence, the impacts of the proposed RTC on the local grid are similar to the current impacts of distributed solar PV, and should not generate more voltage excursions than the current situation with PV only.

V. Discusion and Conclusions

In this paper, we develop a framework for real-time control of distributed residential batteries. The framework proposes a strategy to bid optimal energy quantities on the wholesale energy market. It also includes a novel real-time control algorithm based on MPC to ensure that optimal control decisions are taken locally and maximise local self-consumption. A smart contract is proposed to securely coordinate the fleet of distributed batteries to meet the export commitments from the wholesale energy market. Considering a real use case of 70 households with per-minute consumption and production data from one of the largest-scale smart energy demonstrators in the UK, we show how the proposed framework increases the potential revenues for the owners of the residential batteries. First, compared to a state of the art case where residential batteries are only used for self-consumption at the end-user premises, the return on investment is reduced by almost a half. Then, compared to a case where all the generation assets such as batteries and solar PV would be installed in a central location, the revenues are increased by 35 %. Therefore, our experimental analysis demonstrates that it is more profitable to include residential flexible assets in the portfolio of aggregators than having a portfolio with only production power plants. Furthermore, this framework ensured that more than 60% of the electric consumption of households was supplied from distributed renewable sources owned by the aggregator. Therefore, this framework and the associated RT control algorithm showcase new economic incentives to invest in decentralized renewable generation, which is necessary to meet the UK Government's Net Zero Carbon emission targets. Finally, the robustness of the RTC algorithm to forecast errors and communication latency was also studied and validated.

Acknowledgment

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