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 these asset investments are profitable for their owners requires 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 to meet the market commitments. The framework can apply either to a single prosumer-owned battery, or to a fleet of distributed residential batteries coordinated by an aggregator. It consists of 3 main stages. In the first stage, an optimal day-ahead or intra-day scheduling of the aggregated storage assets is computed centrally. In the second stage, a bidding strategy is proposed for wholesale energy markets. Finally, in the third stage, a 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 algorithm 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 forecast errors and to communication latency is also demonstrated.**

***Index Terms*—Battery management system, distributed generation, smart contract, smart grids**

I. Introduction

NET zero carbon emission schemes usually involve a shift of carbon based energy consumption toward electricity, and an increasing share of electricity generation coming from distributed renewable resources [1]. Economic incentives for renewable energy export to the grid such as Feed in Tariffs (FIT) are gradually removed. This encourages self-consumption of renewable energy at the residential level, which is considerably increased by residential batteries. Yet, residential batteries used solely for self-consumption have a simple payback period above 10 years [2], [3], providing insufficient financial incentives for homeowners. Hence, there has been increasing interest in finding additional revenue streams for residential batteries [4], [5], such as revenues from ancillary services or wholesale energy markets participation [6]. A number of prior works [7]–[11] have considered the participation of batteries in providing ancillary services such as frequency regulation. In our work, motivated by a case study from a large UK smart energy demonstrator based on the Orkney Islands [12], we propose a framework that allows residential batteries to participate in wholesale energy markets, such as day-ahead or intra-day markets. In practice, however, participation in European wholesale markets is generally not open to small assets of power capacity below 1 MW [13]. Hence, there is a need for novel mechanisms to aggregate and control residential batteries to enable wholesale market participation through an aggregator service. In this paper, we propose a control framework that allows an aggregator to coordinate distributed storage assets installed at prosumers premises that are either owned by the aggregator or by the prosumers themselves. Prosumers give their consent to the aggregator to control batteries and participate to the wholesale markets. Therefore, this control must deal with conflicting objectives: at the prosumer level, residential battery control aims to reduce the bill of the household by maximizing self-consumption, whereas at an aggregate or fleet level, the objective is to assure a profitable market participation.

Battery control consists of real-time (RT) decisions to charge or discharge a battery at every time step of the Battery Management System (BMS) controller (from μs to ms). This decision can be performed with a recommendation from an optimised schedule based on forecasts of future production and demand (*optimisation-based control*), or without any recommendation (*heuristic control*). In prior research, the role of the battery has been either to provide grid services such as frequency [8], [9] or local voltage regulation [11], or to optimise the revenues of the battery owner such as a prosumer [14], [15] or an aggregator bidding in the wholesale energy market [6], [7], [15], [16]. Although the topic of batteries for market bidding has been covered in a number of prior works, these mostly consider ancillary services markets or single stand-alone batteries, but not the use of residential batteries for wholesale energy market bidding. Several works, e.g [15], [16], propose solutions for energy market bidding with residential batteries, but they do not address wholesale markets applications.

Some research work take into account uncertainty from changing environments and propose RT operations to ensure that batteries will honour commitments on the wholesale market. However, most of the Real Time Control (RTC) algorithms proposed in the literature apply to the case of grid services optimisation, for which the strategy mostly consists in following either the frequency, or a specific signal from the grid operator [8]–[11]. Hence, only a few works are addressing the problem of real-time control (RTC) for energy markets applications. RTC has been implemented through Model Predictive Control (MPC) [7], [17], [18], or through

heuristic rules [14], [15]. However, except for [7] and [15] that use per second and per minute data for experiments, most of the current research works rely on 15 or 30-minutes resolution data, and do not capture the required granularity for real-time implementations. Moreover, although distributed batteries coordination has been successfully implemented for grid services in [16] and [19], these works assume perfect continuous communication between assets, which does not reflect real-life implementations with residential batteries. Therefore, in this work, we consider per minute data with communication latency above 5 minutes to address realistic scenarios.

Finally, another emerging trend is the use of blockchain technology and smart contracts to enable a decentralised management of energy system assets that does not rely on a single authority or point of failure [20]. For batteries, prior work in [21], [22] implemented a smart contract to store characteristics of batteries such as the state of charge, and to automatically send control recommendations to prioritize the charge of distributed batteries in microgrid applications. They did not consider, however, the aggregation of batteries for market export commitments.

To our knowledge, there is no prior work that addresses the full range of technical challenges of market bidding, coordination and real-time control of a fleet of distributed residential batteries participating in wholesale energy markets. Hence, we design and implement a framework that allows an aggregator of distributed batteries to determine the optimal energy quantities to bid in the wholesale energy market and that ensures these quantities will be honoured by the fleet of batteries. The key novel features of our framework include:

- A wholesale market bidding strategy for an aggregator of residential batteries
- A real-time control (RTC) algorithm based on Model Predictive Control (MPC) embedded in each Battery Management System (BMS)
- A blockchain-enabled smart contracting platform to coordinate the individual batteries exports.

The framework is validated using a real case study from the ReFLEX project [12], one of the largest smart energy demonstrators in the UK, based on the Orkney islands.

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. Framework for Distributed Residential Batteries Control

In this section, we present an overview of the framework designed to control a fleet of distributed residential batteries that makes 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 "Energy as a Service" concept where an energy supplier or aggregator would manage distributed storage assets installed at end-user premises (residential households or commercial buildings for example) to provide cheaper and cleaner energy. The economic objective for the prosumers is to reduce their bill, whereas the supplier or aggregator aims to maximise his 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 [12]. Assets consist in residential or commercial buildings' loads, generation from rooftop solar PV (Photovoltaic) or wind turbines, but also include residential batteries installed at the end-user premises. The aggregator can also integrate his own assets in the assets' portfolio (such as large PV or wind generation). He can then take advantage of these assets to bid energy quantities on the wholesale energy market, from which he generates revenue. Coordination of the batteries to meet the commitment made on the markets is achieved through a dedicated smart contract presented in section III.

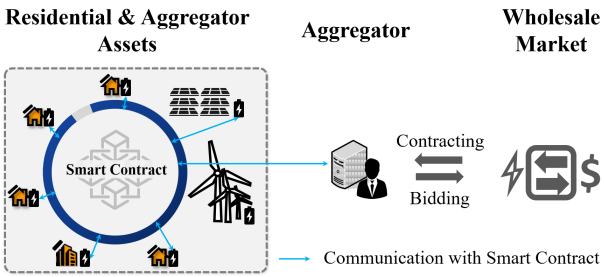


Fig. 1: Use case representation: an aggregator manages distributed assets at households and building premises, but also a wind farm and a solar PV farm.

The control framework can be divided into three main phases as detailed in Fig. 2. In the first phase, based on the forecasts of prices, aggregated demand and production, the aggregator computes the optimal schedule and expected revenue if all assets were not distributed but aggregated into one large load, one large PV and wind generation site, and one large battery. The reason for the aggregation of all the assets is to increase the accuracy of the forecasts.

Computation of the optimal battery schedule and energy quantities' bidding strategy for the wholesale energy market is found by the Mixed Integer Linear Programming (MILP) optimisation problem described in (1), for which each time interval t corresponds to the wholesale market intervals (30 minutes in Europe). A detailed presentation of the optimisation problem can be found in [2].

$$\begin{aligned} \underset{E^t_{B^A_D}, E^t_{B^A_C}, \forall t}{\text{minimize}} \quad & \sum_{t=1}^{T} \left(E^t_{i^A} \pi^t_i - E^t_{e^A} \pi^t_e \right) \\ \text{subject to} \quad & (2),\ (3),\ E^t_{B^A_D}, E^t_{B^A_C}, E^t_{i^A}, E^t_{e^A} \geq 0,\ \forall t, \end{aligned} \tag{1}$$

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 net import and export of the aggregated fleet of assets (residential loads, production and batteries) in

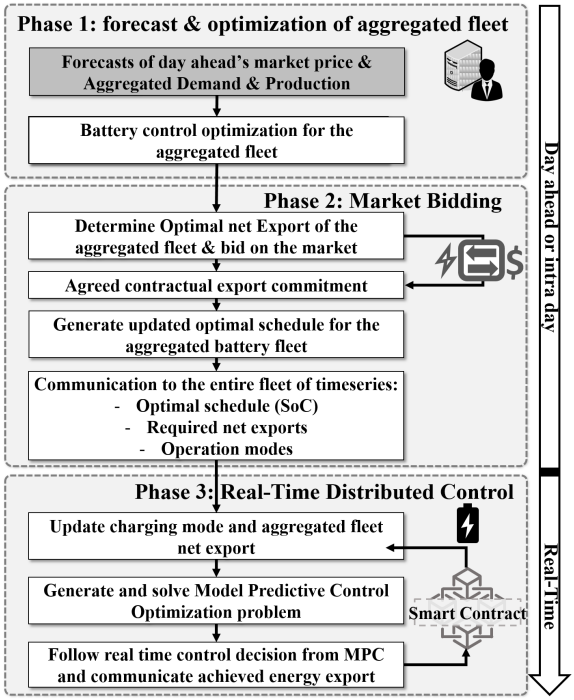


Fig. 2: Framework for the control of distributed residential batteries contributing to the wholesale market.

time interval t. Superscript *A* refers to aggregated quantities. π_i^t is the price of electricity import from the grid and π_e^t is the forecasted wholesale market price for time interval t. Constraint equation (2) corresponds to the energy balance:

$$\begin{aligned} E_{i^A}^t + \eta_d E_{B_D^A}^t - \frac{E_{B_C^A}^t}{\eta_c} &= E_{D^A}^t - E_{P^A}^t \\ E_{e^A}^t - \eta_d E_{B_D^A}^t + \frac{E_{B_C^A}^t}{\eta_c} &= E_{P^A}^t - E_{D^A}^t \end{aligned} \tag{2}$$

where η_d and η_c are the discharging and charging efficiencies of the battery respectively, and $E_{D^A}^t$ and $E_{P^A}^t$ 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). Then, (3) expresses the state of charge (SoC) limits for the aggregated battery capacity and also applies to every time interval t.

$$SoC_{min}^A \leq \sum_{l=1}^{t} \left(E_{B_C^A}^l - E_{B_D^A}^l \right) + SoC^{0,A} \leq SoC_{max}^A, \tag{3}$$

where superscript 0 corresponds to the quantities at the start of the considered period, for $t = 0$. The 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 [23], [24] or K-Nearest Neighbour regressions.

In the second phase, the aggregator uses the optimal resulting schedule $E_{e^A}^t$ to determine the forecasted net exports of the aggregated fleet of assets for the next considered periods (next day in the case of day-ahead markets). The aggregator then places these quantities as bids in the wholesale market. Once the market is cleared, the aggregator receives a preagreed energy schedule. If the contracts differ from the submitted bids, the aggregator will re-run the optimisation of the schedule of the virtual aggregated battery capacity given in (1) based on an updated *price* time-series such that $\pi_e^t = 0$ for all the time intervals t without export contract. Similarly, constraints for the net exported energy $E_{e^A}^t$ must be updated such that $E_{e^A}^t = E_c^t$ when an export contract was awarded, with E_c^t 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 %, (ii) the required aggregated net export quantities E_c^t for the next market periods, and (iii) a *state indicator*, $\mathcal{S}$, that represents the mode of operation of the aggregated battery capacity for every time interval:

$$\mathcal{S} = \begin{cases} 0 & \text{if Battery power matches residual demand} \\ 1 & \text{otherwise.} \end{cases} \tag{4}$$

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 the residential batteries is achieved through a smart contract that ensures that the whole fleet will export the required energy quantities agreed on the wholesale market.

III. Real-Time Control of Distributed Batteries

In this section, we detail the RTC algorithm that runs in every battery's BMS and the smart contract operations.

A. Model-Predictive Control Algorithm

In this Model Predictive Control (MPC) implementation for distributed batteries, each BMS solves a local optimisation problem at regular time intervals t_j (e.g. $t_{j+1} - t_j = 2$ min in our simulations) specified in (6) for the rest of the considered market time interval. Because this time horizon can be up to 30 minutes ($t - t_j$), the MPC optimisation problem aims to determine an optimal battery schedule ($E_{B_{C,D}^k}^{t_{j+1}}, E_{B_{C,D}^k}^{t_{j+2}}, ...E_{B_{C,D}^k}^{t}$) with large time steps equal to $t_{j+1} - t_j$. Hence, it does not correspond to a RT schedule with RT time steps t_s that are in the order of the μs or ms. Between two consecutive optimisations that would occur at times t_j and t_{j+1} respectively, the BMS will take N_s operational decisions (charging/discharging) that correspond to the recommendation from the first step of the optimal schedule ($E_{B_{C,D}^k}^{t_{j+1}}$), 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 BMS. 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 $E_{B_{C,D}^k}^{t_{j+1}}$, which is the first step of the optimal schedule.

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

$$\underset{E^l_{B^k_D}, E^l_{B^k_C}, \forall l}{\text{minimize}} \quad \sum_{l=t_{j+1}}^{t} E^l_{i^k}\pi^l_i + (1-\varepsilon_{RE})E^l_{e^k}\pi^l_e + \mathcal{S}^t(1-\varepsilon^2_{RE})\frac{SoC^{t,A}-SoC^{t,k}}{SoC^k_{max}} + \varepsilon_{RE}\frac{\left|RE^{t,k} - \sum_{l=t_{j+1}}^{t}\left(E^l_{e^k} - E^l_{i^k}\right)\right|}{E_{max}} \tag{6}$$

$$\text{subject to} \quad (2),\ (3),\ E^l_{B^k_D}, E^l_{B^k_C}, E^l_{l^{i^k}}, E^l_{e^k} \geq 0,\ \forall l.$$

time interval, corresponds to the time horizon for the MPC optimisation. t_{sc} is the time at which each BMS sends and receives the last information to/from the smart contract (for example $t_{sc} - t_{sc-1} = 5$ min). t_j is the time at which MPC optimisations are executed (every 2 minutes for example). Finally, the smallest time step t_s (displayed in grey in Fig. 3) corresponds to the cycle time for BMS RT operations (for example, $t_s - t_{s-1} = 200\mu$s).

At the beginning of each market time interval t, the BMS initializes $RE^{t,A}$ (the remaining net export required from the whole fleet) with the value that was communicated originally by the aggregator. For intervals where no contract was agreed, $RE^{t,A}$ is set equal to 0. At every communication time with the smart contract t_{sc}, each BMS receives an updated value of $RE^{t,A}$ that can be negative if the fleet produced more than what was needed. Along with $RE^{t,A}$, the smart contract communicates 2 weights values w^k_e and w^k_i to each battery 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 battery k for the rest of time interval t. The details of the weights computation are provided in the next subsection. With these information, each BMS updates $RE^{t,k}$, the remaining net export required from the battery k before the end of the market interval:

$$RE^{t,k} = \begin{cases} RE^{t,A}\cdot w^k_e - \sum_{l=t_{sc}}^{t_j}\left(E^l_{e^k} - E^l_{i^k}\right), & \text{if } RE^{t,A} \geq 0 \\ RE^{t,A}\cdot w^k_i - \sum_{l=t_{sc}}^{t_j}\left(E^l_{e^k} - E^l_{i^k}\right), & \text{otherwise,} \end{cases} \tag{5}$$

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 BMS also computes a forecast of the household's future consumption and production for the remainder of the current market interval. In our simulations, the BMS generates a forecast with 15 minutes time steps. Although forecast algorithms are beyond the scope of this paper, our experiments showed that Linear Regression demonstrated the best compromise between speed and accuracy for forecasts of up to 1 hour ahead.

The MPC optimisation problem formulation is shown in (6), where the objective function 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. It also includes the SoC recommendation $SoC^{t,A}$ and net export requirements $RE^{t,k}$. It is good practice to make sure that the SoC target $SoC^{t,A}$ and net export target $RE^{t,k}$ are feasible by coercing them into achievable values. As mentioned above, t is the current market time interval, $t_j \in [0, t]$ is the time at which the optimisation is run, 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 (4). $SoC^{t,k}$ 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 (5). Finally, $\left(E^l_{e^k} - E^l_{i^k}\right)$ corresponds to the net export from household k at time l, and is determined by (2).

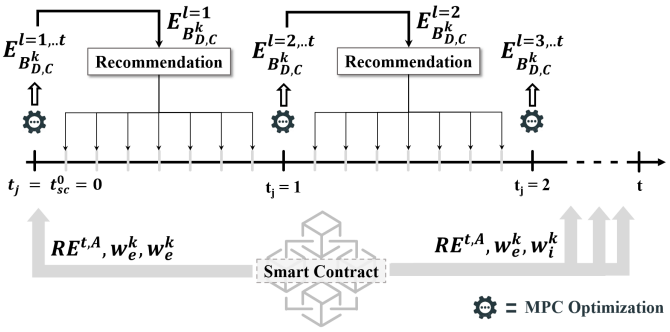


Fig. 3: MPC process with smart contract communication.

This MPC formulation also corresponds to a MILP formulation where the absolute value in (6) is achieved by introducing a positive auxiliary variable $x \geq \left|RE^{t,k} - \sum_{l=t_{j+1}}^{t}\left(E^l_{e^k} - E^l_{i^k}\right)\right|$.

The solution of the optimisation consists in an optimal battery schedule given by $E^{l=t_{j+1},\ldots,t}_{B^k_{C,D}}$. As shown in Fig. 3, the BMS uses the first charging and discharging energy quantities $E^{l=t_{j+1}}_{B^k_{C,D}}$ from the optimal schedule to provide a recommendation for the battery power $P^s_{B^k}$ at every time step t_s of the BMS operation between t_j and t_{j+1}. $P^s_{B^k}$ is the power of the battery cells, and is positive (negative) when the battery is charging (discharging):

$$P^s_{B^k} = \begin{cases} \eta\left[P^{t_s}_{P^k} - P^{t_s}_{D^k}\right], & \text{if } E^{t_{j+1}}_{B^k_C} - E^{t_{j+1}}_{B^k_D} = \eta\left[E^{t_{j+1}}_{P^k} - E^{t_{j+1}}_{D^k}\right] \\ \frac{E^{t_{j+1}}_{B^k_C} - E^{t_{j+1}}_{B^k_D}}{s\cdot N_s}, & \text{otherwise,} \end{cases} \tag{7}$$

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

$$\eta = \begin{cases} \eta_c, & \text{if } P^{t_s}_{P^k} - P^{t_s}_{D^k} \geq 0 \\ \dfrac{1}{\eta_d}, & \text{otherwise.} \end{cases} \tag{8}$$

B. Smart Contract Platform

A blockchain-enabled smart contract between the aggregator and all the fleet of distributed batteries coordinates their operation and ensures that contractual export commitments E_c^t to the wholesale market are met. It also coordinates the sharing of energy surpluses within the fleet. The smart contract represents a distributed and tamper-proof way that increases the reliability and security of the coordination by removing a single point of failure, and by improving resilience to cyber-attacks, as opposed to a centralized operation realised by a single server. Furthermore, it allows for automatic self-verification of commitments and exports of the fleet of batteries that does not rely on a single aggregator authority.

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. Each battery is associated with an account, similar to the aggregator, who deploys and manages the smart contract and associated operating fees, as shown in Fig. 4. The functions implemented in the smart contract are

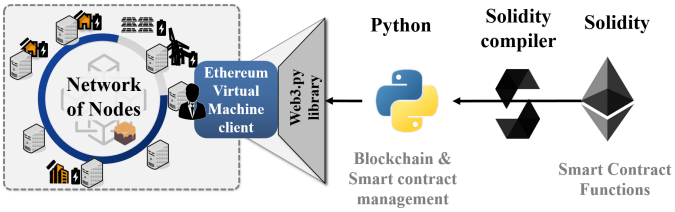


Fig. 4: Local smart contract implementation for distributed batteries coordination. The deployment and management of the smart contract is detailed for the aggregator node.

listed below:

- Constructor, to initialize the contract.
- Register a new household.
- Update the time series sent by the aggregator $(SoC^{t,A}, E_c^t, \mathcal{S}^t)$.
- Update a household information: $SoC^{t_{sc},k}$ the battery SoC at the current time, $E_e^{t_{sc},k}$ the energy exported/imported by household k since the last communication between the battery k and the smart contract, and $E_e^{t,k}$ 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 $E_e^{t_{sc},k}$.
- Compute the batteries weights w_i^k and w_e^k for all the batteries k. The weights are computed as follows:

$$w_e^k = \frac{W_e^k}{\sum\limits_{k \in households} W_e^k}\ ,\ w_i^k = \frac{W_i^k}{\sum\limits_{k \in households} W_i^k} \tag{9}$$

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

$$W_e^k = \begin{cases} SoC^{t_{sc},k} & \text{if } E_e^{t_{sc},k} \geq 0\ ,\ SoC^{t_{sc},k} \geq SoC^{t,A} \\ 0 & \text{Otherwise.} \end{cases} \tag{10}$$

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

$$RE^{t,A} = E_c^t - \sum_{k \in \text{households}} E_e^{t,k}. \tag{11}$$

- Provide the required information to all registered households using the emit method: $RE^{t,A}, w_e^k, w_i^k$.

The cost of this smart contract for a battery is around 105957 gas units, which corresponds to 0.002 ether or 0.7$ if the contract runs on an Ethereum Blockchain. However, this cost can be reduced to only the nodes operation costs if the smart contract is realised on a real-world private and permissioned blockchain.

IV. Experimental validation

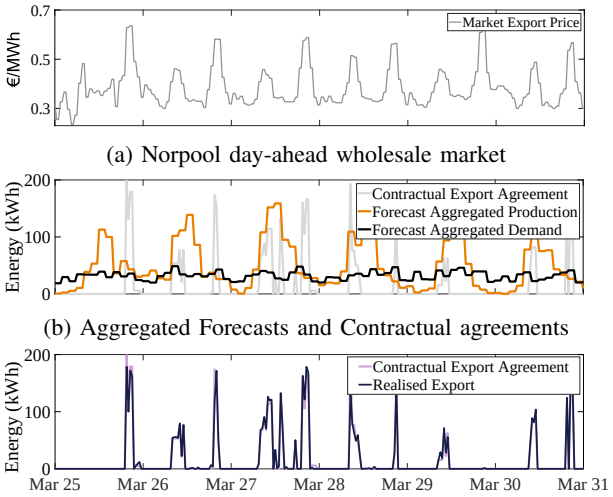
A. Experimental set-up and case study

The proposed framework was implemented for the use case described in section II, that reflects the settings of our large-scale demonstrator [12]. An aggregator invests in distributed residential batteries and generation assets (rooftop PV or wind turbines), when households do not have any already, and installs those at customers' premises. 70 households were considered in this study, each of them with a micro-generation asset (solar PV or micro wind) and a residential battery [25]. To have a more general case, we also consider that the aggregator already owns large generating assets that include one PV power plant of 105 kW and one wind farm of 130 kW. The data used for the demand and production profiles are minutely data from real measurements gathered in real households participating in the ReFLEX project [12]. The pricing data for the wholesale market price have been extracted from Nordpool's day-ahead market [26]. Retail import prices follow dynamic Time of Use (ToU) pricing scheme from [27]. Market time interval is 30 minutes. Hence, the day-ahead optimisation uses time steps of 30 minutes. We do not consider export tariff for households (such as FiT), as these incentives have been removed in the UK. In real-life applications, forecasts errors and communication latency can lead RT operations to achieve different export energy quantities than the contractual agreement. In this case a penalty applies to the aggregator, that is equal to the product of the energy quantity difference and an imbalance price. Imbalance prices are computed by the system operator and depend on the system's frequency. In this work, we use imbalance prices from European markets [28]. Also, we consider that the fleet is linked by a virtual private wire contract [29]. In this virtual private wire configuration, 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 [30]. The experimentation was conducted for one calendar month.

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. Day-ahead forecasts for the aggregated demand and production were generated using the real data multiplied by a random variable uniformly distributed to simulate an uncertainty of 25% around the real value. The time interval between two forecast values was 2 hours.

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 contracted in the wholesale market. Finally, Fig. 5.c compares this contractual energy export quantities with the realised export of the aggregated fleet. The achieved 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. Indeed, the SoC of the household with wind generation is different than the SoC of batteries in households owning solar PV generation. We also assess the economic benefits that an aggregator can expect from the proposed framework. The source of revenues for the fleet are the revenues from energy exports agreed on the wholesale energy market and the total bill reduction of the households. The bill reduction is computed as the total bill difference between the baseline scenario (Scenario 0 defined below) without distributed generation (battery and rooftop PV or wind) and the total bill after the framework is implemented. Based on the ReFLEX demonstrator project, a number of scenarios have been considered for comparison:

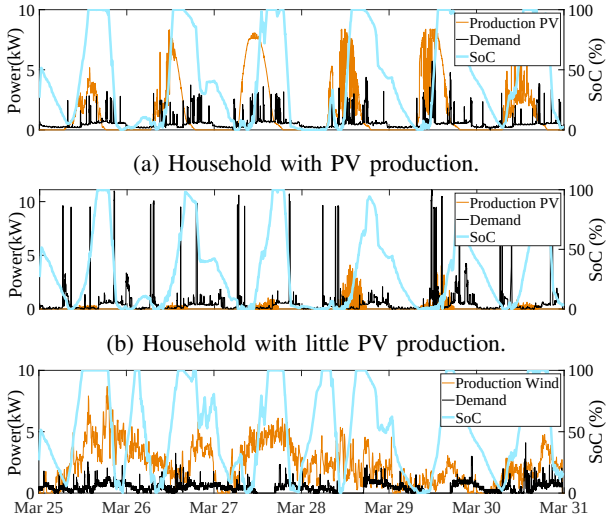


(a) Norpool day-ahead wholesale market

(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.

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 PV or wind asset and a residential battery, but without any aggregator and without any revenue from energy exports to the grid. The batteries are individually controlled using a RT *heuristic* based algorithm embedded in each BMS. This algorithm charges the battery when the household produces more energy than it consumes, and discharges the battery when the household consumes more than it produces. It provides similar revenues as an optimisation-based algorithm when batteries do not export to the grid [2].

Scenario 2 considers an aggregator with all the generation assets installed in the same location (PV, wind and a single large battery co-located with the proposed RTC algorithm) and not distributed in individual households. Households' demands are not included in the aggregator's portfolio for this scenario. Hence, 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: the aggregator can bid 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 [30]) when centralised generation assets export.

Scenario 4 considers distributed residential assets with an aggregator that bids on the 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 I 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 in each scenarios depend on the cost of storage assets which is beyond the scope of this paper. Table I shows that the proposed RTC algorithm for distributed batteries in Scenario 4 provides the greatest revenues to the fleet. It shows that bidding on the market while taking advantage of distributed residential generation for self-consumption allows an aggregator to increase its revenues by 7% compared to Scenario 3 in which the aggregator invests in the same quantity of assets, but installs all of them at the same location. This is due to the fact that in the case of centralized generation

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

Scenario	Bills Reduction (€)	Market Revenue (€)	Total Revenue (€)
0	0	0	**0**
1	2258	0	**2258**
2	0	3025	**3025**
3	2911	909	**3820**
4	3208	891	**4099**
5	1127	0	**1127**

assets (Scenario 3), electricity imports from households always include a network cost (48 % of the import tariff) that does not apply in Scenario 4 when households consume their own production. Given the forecast uncertainty and communication latency considered in Scenario 4, the performance of the proposed RTC algorithm is demonstrated. Furthermore, using distributed residential batteries with the proposed algorithm provides a revenue increase of 35% compared to Scenario 2 in which an aggregator does not include households demand in his portfolio and only owns generation assets (PV, wind generation and batteries) co-located in one central location. This shows that it can be profitable for investors to support self-consumption by investing in decentralized generation assets with an aggregator for market bidding. Similarly, comparison between Scenario 1 and 4 shows that it can be profitable for prosumers to allow an aggregator to control their assets to generate extra revenue. Finally, this study also shows that the proposed RTC algorithm increases the self-consumption rate of end-users: the average self-consumption of individual households was increased from 28% in a scenario with only micro-generation (Scenario 5) to 64% in scenario 4 with the proposed framework.

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 stay above 3300 €, which makes the distribution of micro-generation assets more profitable than Scenario 2.

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 4220 € for 1 min communication time interval to 3750 € for 15 min. Although shorter communication time intervals provide greater revenues, they also increase the operation cost of the smart contract.

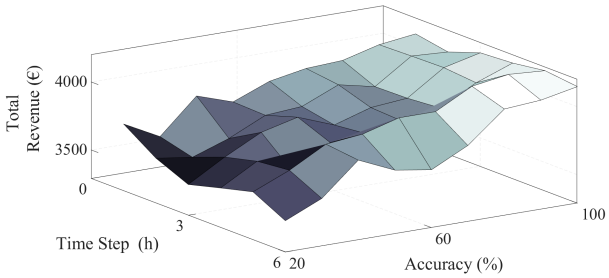
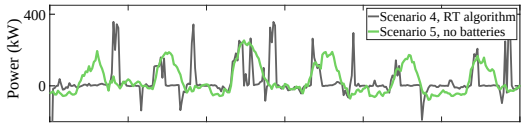


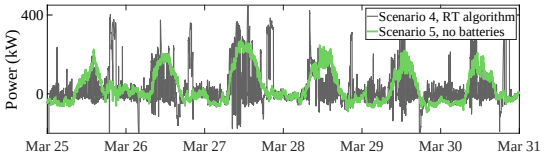
Fig. 7: Total monthly revenues of the fleet obtained for different forecast accuracies and time steps.

D. Impacts for the grid

Finally, we study the impact of the proposed battery control on the electricity grid. Fig. 8 shows the net power profiles of the aggregated fleet for 30 minutes and 1 minute time intervals for scenario 4 and in Scenario 5. The profile of the aggregated fleet with batteries (Scenario 4) is relatively flat when measured on a 30 minutes basis (Fig. 8.a), except for periods when export is incentivized by the grid. However Fig. 8.b shows that the actual profile on a per minute basis is much more noisy with one important peak per market interval to compensate for extra production or demand. Similarly, the monthly Peak to Average Ratio (PAR) is 3 times higher for Scenario 4 than for the case without batteries (Scenario 5), which is due to an increase of the maximum power exported and to a decrease of the average power consumption in Scenario 4. This effect could be limited by considering grid services in the MPC optimisation.



(a) 30 min time interval measurements.



(b) 1 min time interval measurements.

Fig. 8: Net power profile of the aggregated fleet of assets for Scenario 4 and 5.

Finally, Fig. 9 compares the PAR before and after the installation of the batteries. Although the average PAR for scenario 4 is slightly greater than the PAR before batteries were installed, they are comparable in both scenarios. Hence, the impacts of the proposed RTC on the local grid are similar to the current impacts of distributed solar PV.

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 real-time control algorithm

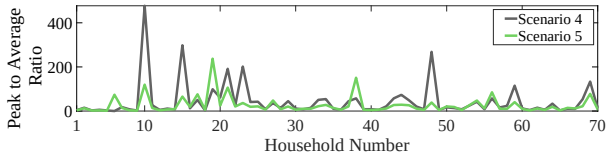


Fig. 9: Comparison of Peak to Average Ratio for scenario 4 and scenario 5 for all considered households.

based on MPC to ensure that optimal decisions are taken locally by maximizing 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 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 that the proposed framework increases by 7% the potential revenues for the owner of the residential batteries compared to a case where all the batteries are installed in a central location. It also demonstrates that it becomes more profitable to include residential flexible assets in the portfolio of aggregators than having a portfolio with only production power plants as in our use case, it increased the revenues of the considered community by 35%, and it ensured that more than 60% of the electric consumption was produced from distributed renewable sources owned by the aggregator. Therefore, this framework showcases new economic incentives to invest in decentralized renewable generation, which is necessary to meet the objectives of UK government's Net Zero Carbon emission schemes. The robustness of the RTC algorithm to forecast errors and communication latency is also studied and validated. Finally, although the impacts of this algorithm on the grid are not negligible at the system level, they could be mitigated by including grid services in the batteries operations.

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