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Power Cloud Framework for Prosumer Aggregation to Unlock End-User Flexibility

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Abstract: The behind-the-meter technologies integrating "all-in-one" photovoltaic plants, storage systems, and other technological solutions can transform consumers into active prosumages to both reduce their energy costs and provide flexibility to the grid. To exploit those flexibility services, it is necessary to manage the end-users in an aggregated form. End-user aggregation is currently becoming a suitable solution to manage energy flows to obtain environmental, economic, and social benefits. In this scope, the paper presents an algorithm to opportunely manage the energy flows inside this aggregation operating in a Power Cloud framework. The algorithm schedules the energy flows that the end-user storage systems must exchange inside the aggregation to maximize the use of renewable sources, provide grid flexibility services, and simultaneously provide balancing services. The algorithm is organized into three different steps: the day-ahead step, the real-time step, and the balancing one. Some simulation results are illustrated to demonstrate the effectiveness of the proposed algorithm.

Keywords: power cloud; energy aggregation; energy management

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Citation: Brusco, G.; Menniti, D.; Pinnarelli, A.; Sorrentino, N.; Vizza, P. Power Cloud Framework for Prosumer Aggregation to Unlock End-User Flexibility. *Energies* **2023**, *16*, 7071. https://doi.org/10.3390/en16207071

Academic Editor: Enrique Romero-Cadaval

Received: 2 August 2023
Revised: 29 September 2023
Accepted: 11 October 2023
Published: 12 October 2023

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1. Introduction

The widespread presence of both prosumers and prosumages (a prosumage is a prosumer integrating a storage system) allows the implementation of several solutions to reduce the cost of energy and to provide grid flexibility services in the energy transition scenario.

There are some studies in the literature that provide analysis concerning the participation of end-user aggregation in providing services to the transmission or distribution grids. In [1], the authors introduce the concept of a distributed resource aggregator, which is an active part of the distribution system that enables small resources to participate in the electricity market, providing ancillary services. In this framework, the aggregator covers the role of a system coordinator. In [2,3], the aggregation of electric vehicles (EVs) to provide ancillary services in the presence of V2G (vehicle-to-grid) charging stations is considered. In particular, in [2], real-time EV charging controllers allowing participation in the ancillary services markets have been implemented. One of the parameters utilized is the charging efficiency. In [3], the EV aggregations provide a secondary frequency response considering the EV user's preferences.

The management of the aggregation to reduce congestion and provide flexibility using distributed energy resources is also an important issue. In [4], a heuristic dispatching approach is used. In [5], distributed resources are involved in providing voltage support and optimizing real-time operations in the distribution and transmission networks.

The aggregation can provide services to the grid both using storage systems and by opportunely managing the loads in real-time or scheduling them in advance. In [6–8], home appliances are considered flexible resources to provide services to the grid if they are required; algorithms to manage them in real-time for a 24-hour time horizon are also implemented. This operating mode can lead to modifying the users' habits or, in any case, can require the user's interaction, often leading to the impossibility of providing flexible services with the possibility of penalties for the aggregator, as in [9]. On the contrary, if energy storage systems (ESSs) are used, several features can be carried out without requiring users' interaction [10,11].

In [12], a review of the different management models of storage systems is carried out. It is highlighted how, among the different dispatching domains, between financial and technical, the financial one is the most requested and used by users who require greater profits. On the contrary, the technical ones are most requested by network operators. In the model that will be discussed in this paper, a technical approach has been considered, but without neglecting the financial one, considering the earning possibilities for the users themselves that will interact with the grid operator. Different from other methods, this one considers both users and grid necessities.

In [13], an energy management system for the minimization of the daily cost of energy and the maximization of self-consumption for a community microgrid is discussed. It is shown how the participation of a community microgrid allows it to have significant economic benefits. Such benefits are also increased using a peer-to-peer (P2P) mechanism.

In [14], a two-stage approach is proposed to manage a community, allowing separate energy management operations and economic aspects; they show that in the French framework, the user's bill savings belonging to the community are 10% more convenient compared to the users not belonging to the community.

In [15], an examination of the possible aggregation of users and how they can be managed is performed. Among the different models, the flexibility of aggregation has been introduced. Since market access is difficult for small consumers, the implementation of aggregations allows them to access the market and, at the same time, provide flexible services to the grid.

In [16], an energy management approach is presented. The main characteristic is that it is based both on a minimization cost algorithm and, at the same time, integrates a demand-side approach.

In [17], an energy management strategy that uses fuzzy logic to allocate electricity to hydrogen storage and electricity storage is proposed. It is applied to a near-zero-energy community. The proposed multi-objective optimization strategy allows for a percentage greater than 80% of renewable energy. In [18], an aggregation of users is considered, and an approach to managing the internal microgrids is presented. In particular, the internal aspects, from different points of view—market, environmental, and economic—are examined. In this energy management strategy, a dispatchable biomass plant is considered to increase flexibility.

To provide flexibility services, it is necessary to forecast the available flexibility. The purpose of [19] is to predict the flexibility of a local energy community (LEC), so the use of power consumption of controllable loads is useful to this aim. Such available flexibility was predicted using a particular artificial neural network (ANN).

1.1. Contribution of the Paper

This paper, starting from the concept of Power Cloud [20] and its related advantages, proposes an algorithm to opportunely manage the energy flows inside an end-user aggregation from day-ahead to real-time. The Power Cloud concept is a solution to facilitate the integration of distributed renewable energy systems with new environmentally friendly and smart enabling technologies for final end-user active participation. Specifically, distributed flexibility resources, such as storage systems, are managed to maximize the use of RES and provide transmission system operator (TSO) and/or distribution system operator (DSO) ancillary services. At this scope, EVs may also be easily introduced into the algorithm as other flexibility resources, like those considered by the authors in [21].

The proposed algorithm is organized in three steps: the day-ahead step, the real-time step, and the balancing one. The first one determines the charge/discharge of storage systems present in the aggregation to maximize the renewable energy prosumers/prosumages self-consumption using forecasted hourly production and consumption. A reference power profile is determined to exchange with the grid. The second one determines in real-time how to modify that profile if flexibility services are required by the TSO/DSO, and in the last step, the third one, to compensate for errors in forecasting production and/or consumption. Differently from [22,23], where particular bidding and optimization strategies are proposed to work in real-time in the reserve market, the proposed algorithm operates in a deterministic way under the existing electricity market rules.

The implemented algorithm is divided into steps that can operate separately, and one of its advantages is that it does not strictly need field communication among and with end-users to operate. Indeed, if some communication problems occur, it keeps working, still guaranteeing acceptable results; only the balancing action needs measurements from the field. Another advantage is that the algorithm can be implemented on a management platform with relatively low computational efforts if the platform that enables the exchange of data, mainly the charge/discharge of the storage systems between the aggregator and end-users, is blockchain-based in order to assure transparency, immutability, and security [20].

1.2. Structure of the Paper

This paper is structured in four sections. After a summary of the principal issue to be faced, Section 2 describes some aspects concerning end-user aggregation. Sections 3 and 4 describe, respectively, the day-ahead and real-time steps of the proposed algorithm, with a specific focus on the balancing one. In Section 5, a case study and the related simulation results are illustrated and discussed.

2. Technical and Economic Issues of Power Cloud Management Model

The end-user aggregations are new energy management models to produce, consume, and share energy in the Power Cloud framework as proposed in [20]. The end-users virtually operate within a geographical local perimeter to reduce the energy exchange outside the aggregation and maximize its economic, environmental, and social benefits.

To allow them to achieve those benefits, the implementation of the proposed algorithm must consider the electricity and energy market framework and its rules.

For most of the structure of the electricity markets in Europe, it is necessary to define in advance the energy schedule for both injected and absorbed power, the so-defined day-ahead schedule of the exchanged power. Specifically, in the presence of renewable energy sources, it is necessary to schedule their production.

At the same time, considering that the ESSs are the most important resources to provide grid flexibility services [20], it is necessary to define in advance the flexibility schedule that they can offer. It is equally important to have a day-ahead schedule of the power that the ESSs may exchange to maximize the use of the energy produced by renewable sources.

To this purpose, two issues must be faced: the first is the use of accurate consumption and production forecasting algorithms to evaluate a reliable power profile schedule and avoid power imbalances between the scheduled and real power profiles; the second is to have reliable measures from the field in terms of the power produced by all renewable energy sources, absorbed by the loads, exchanged with the grid and with the ESS, and the state of charge (SOC) of the ESSs.

For the first issue, there are several studies that correlate the positive effect of forecasting models with imbalance charges [21]. In this paper, the forecasting algorithm described in [24] is used to forecast PV power production. Moreover, the balancing step is introduced to compensate for possible forecasting errors that may occur and to avoid charges for not having fulfilled the undertaken commitments.

For the second issue, although the above-mentioned measures do not intervene in the day-ahead step, they become necessary in the balancing step. For this reason, the use of a smart meter with a small measurement time range (from minutes up to a few seconds) is assumed.

3. Power Cloud Day Ahead Energy Management Algorithm

The aim of the proposed algorithm is the optimal use of renewable energy source generation inside an end-user aggregation in a Power Cloud framework, with the possibility of providing grid flexibility services. The management algorithm consists of a three-step algorithm. The first step is the day-ahead step (DA), which receives as input the consumption and production forecasts, as well as the forecasts of the ESS SOC. It provides the scheduling of power and the availability of flexibility services, sharing both the surplus and deficit of energy among the end-users equipped with the ESSs. Starting from the DA results, the real-time algorithm (RTA) is processed. It considers the flexibility requests sent by the grid operator, and it operates for each hour using the results of the first step, changing the scheduled power profile. In this step, the flexibility services, determined by the availability of ESS, are offered, processed, and executed. In the end, based on the real measures of the exchanged power and of the storage system parameters, the third step, the balancing step, operates in real time to reduce any imbalance between the scheduled power profile and the real one.

3.1. Day-Ahead Step

The day-ahead step operations are illustrated in Figure 1. It consists of many functions that are carried out, one in sequence to the next, starting from the forecasting of production and consumption for the single users, aggregating them until the exchange of battery profiles and the availability to provide services to the grid are calculated. Such operations are represented by different equations that are reported below.

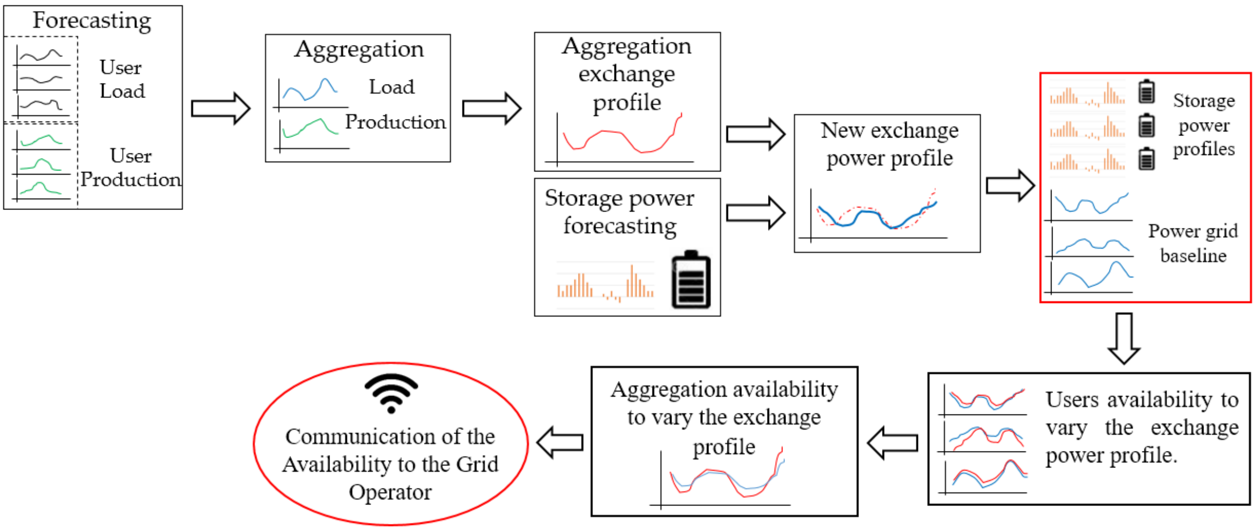

Figure 1. Day-ahead step flow chart.

Let us consider an aggregation of n end-users: n_p is the number of end-users equipped with a PV plant, n_c is the number of consumers, and n_s is the number of end-users equipped with an ESS.

Starting from n_p hourly energy production forecasts $\left(E^{f,u}_{p,h}\right)$ and n_c hourly energy consumption forecasts $\left(E^{f,u}_{c,h}\right)$, the aggregated hourly energy consumption and production forecasts, respectively, $E^{f}_{c,h}$and $E^{f}_{p,h}$, are obtained.

$$E^{f}_{c,h} = \sum_{u=1}^{n_c} E^{f,u}_{c,h} \quad (1)$$

$$E^{f}_{p,h} = \sum_{u=1}^{n_c} E^{f,u}_{p,h} \quad (2)$$

The exchange energy profile with the grid for each end-user ($E^{f,u}_{ex,h}$) and for the aggregation ($E^{f}_{ex,h}$) can be obtained as the difference between production and consumption.

$$E^{f,u}_{ex,h} = E^{f,u}_{p,h} - E^{f,u}_{c,h} \quad (3)$$

$$E^{f}_{ex,h} = E^{f}_{p,h} - E^{f}_{c,h} \quad (4)$$

Using the rated capacity of each ESS and their *SOC* forecast for the last hour of the day before ($SoC^{f,u}_{24}$), the energy that can be stored in the ESS for each end-user ($E^{f,u}_{av,ch}$) and for the aggregation ($E^{f}_{av,ch}$) is determined.

$$E^{f,u}_{av,ch} = C^{u} \cdot \left(1 - SoC^{f,u}_{24}\right) \quad (5)$$

where C^u is the capacity for each *ESS*.

The hourly energy surplus ($E^{f,u}_{sur,h}$) and deficit ($E^{f,u}_{def,h}$) for the day ahead are determined for each end-user.

$$E^{f,u}_{sur,h} = E^{f,u}_{p,h} - E^{f,u}_{c,h} \qquad if \ \left(E^{f,u}_{p,h} - E^{f,u}_{c,h}\right) > 0 \quad (6)$$

$$E^{f,u}_{def,h} = E^{f,u}_{c,h} - E^{f,u}_{p,h} \qquad if \ \left(E^{f,u}_{p,h} - E^{f,u}_{c,h}\right) < 0 \quad (7)$$

At the same time, the daily energy surplus $\left(E^{f,u}_{sur,d}\right)$ for each end-user and for the aggregation is obtained $\left(E^{f}_{sur,d}\right)$.

$$E^{f,u}_{sur,d} = \sum_{h}\left(E^{f,u}_{p,h} - E^{f,u}_{c,h}\right) \quad if \ \left(E^{f,u}_{p,h} - E^{f,u}_{c,h}\right) > 0 \quad (8)$$

$$E^{f}_{sur,d} = \sum_{u=1}^{n} E^{f,u}_{sur,d} \quad (9)$$

Similarly, the energy deficit for each end-user ($E^{f,u}_{def,d}$) and for the aggregation ($E^{f}_{def,d}$) can be determined.

$$E^{f,u}_{def,d} = \sum_{h}\left(E^{f,u}_{c,h} - E^{f,u}_{p,h}\right) \quad if \ \left(E^{f,u}_{p,h} - E^{f,u}_{c,h}\right) < 0 \quad (10)$$

$$E^{f}_{def,d} = \sum_{u=1}^{n} E^{f,u}_{def,d} \quad (11)$$

Once such variables have been determined, at this point, it is necessary to calculate opportune distribution coefficients to maximize the amount of energy to be shared among the n end-users. These distribution coefficients (F^{u}_{d}) are determined starting from $E^{f,u}_{av,ch}$, referred to each end-user equipped with an ESS. Defining $E^{f}_{av,ch}$ the overall available charging energy for the aggregation, F^{u}_{d} is determined as the ratio between $E^{f,u}_{av,ch}$ and $E^{f}_{av,ch}$.

$$E^{f}_{av,ch} = \sum_{u=1}^{n} E^{f,u}_{av,ch} \quad (12)$$

$$F_d^u = \frac{E_{av,ch}^{f,u}}{E_{av,ch}^{f}} \tag{13}$$

An example of F_d^u calculation is reported in Figure 2. Five different end-users equipped with ESS are considered. The ESSs have different *SOCs* and capacities. The values of F_d^u are determined and reported.

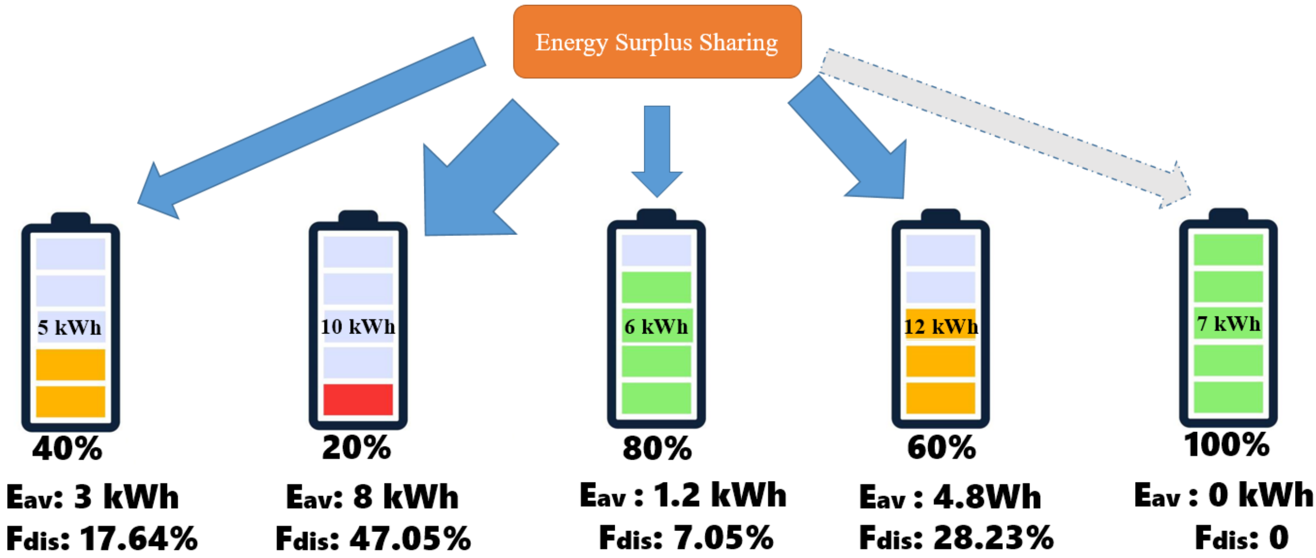

Figure 2. An example of distribution coefficients (F_d^u) calculations.

Such distribution coefficients are used to determine the energy that each end-user u has to store during the following day ($E_{crg,d}^{f,u}$); it will be function both of $E_{sur,d}^{f}$ and of $E_{av,ch}^{f,u}$. It is defined as:

$$E_{crg,d}^{f,u} = \min\left(F_d^u \cdot E_{sur,d}^{f},\ E_{av,ch}^{f,u}\right) \quad \forall\ u \in aggregation \tag{14}$$

Once $E_{crg,d}^{f,u}$ has been calculated, the power profiles that each end-user has to exchange with the ESS are available. The energy profile for the ESS ($E_{bat,ch,h}^{f,u}$) is obtained considering the distribution coefficient F_d^u in (11) and the aggregation hourly energy surplus ($E_{sur,h}^{f}$) if it exists.

$$E_{sur,h}^{f} = \sum_u \left(E_{p,h}^{f,u} - E_{c,h}^{f,u}\right) \tag{15}$$

$$\text{where, } if\ E_{sur,h}^{f},\ E_{crg,d,res}^{f,u}, > 0$$

$$E_{bat,ch,h}^{f,u} = \min\left(E_{sur,h}^{f} \cdot F_d^u,\ E_{crg,d,res}^{f,u}\right) \tag{16}$$

where $E_{crg,d,res}^{f,u}$ is calculated iteratively as follows:

$$E_{crg,d,res}^{f,u} = E_{crg,d}^{f,u}\ for\ h = 1 \tag{17}$$

$$E_{crg,d,res}^{f,u} = E_{crg,d,res}^{f,u} - E_{bat,ch,h}^{f,u}\ \ for\ h > 1 \tag{18}$$

If the hourly aggregate energy production profile is lower than the aggregate consumption energy profile, an energy deficit occurs ($E_{def,h}^{f} > 0$). Thus, the energy that the ESS must supply is calculated ($E^{f,u}_{bat,ds,h}$) as in (15). Only the load of the end-users equipped with the ESS can be supplied by that ESS. The $E^{f,u}_{bat,ds,h}$ is determined as the minimum between $E^{f,u}_{def,h}$ and the residual energy in the ESS that is useful to supply the load ($E^{f,u}_{dis,res,h}$). Naturally, it can be defined only if the $SOC^{f,u}_{h}$ of the ESS is greater than the minimum admissible value of SOC (SOC_{min}).

$$E^{f,u}_{bat,ds,h} = \min\left(E^{f,u}_{def,h},\ E^{f,u}_{dis,res,h}\right) \tag{19}$$

$$\text{where,} \quad if \ \left(E^{f,u}_{c,h} - E^{f,u}_{p,h}\right) > 0$$

$$E^{f,u}_{def,h} = E^{f,u}_{c,h} - E^{f,u}_{p,h} \tag{20}$$

$$\text{and } E^{f}_{def,h} = \sum_{u=1}^{n} E^{f,u}_{def,h} \tag{21}$$

$$E^{f,u}_{dis,res,h} = \left(SOC^{f,u}_{h} - SOC_{min}\right)\cdot C^{u} \tag{22}$$

$$SOC^{f,u}_{h+1} = SOC^{f,u}_{h} + \left(E^{f,u}_{bat,ch,h} - E^{f,u}_{bat,ds,h}\right)/C^{u} \tag{23}$$

The baseline grid power exchange profile ($E^{f,u}_{grid,h}$), with an hourly time step, can be defined for each end-user and for the entire aggregation.

$$E^{f,u}_{grid,h} = E^{f,u}_{c,h} - E^{f,u}_{p,h} + E^{f,u}_{bat,ch,h} - E^{f,u}_{bat,ds,h} \tag{24}$$

At this point, the flexibility and availability of the single end-user must be estimated. At this scope, a fundamental assumption is that only the reduction of the baseline can be carried out, so the hours where $E^{f}_{def,h}$ is greater than zero are considered. The number of hours when $E^{f}_{def,h} > 0$ is calculated (n_{def}). It is used to determine the hourly energy amount that end-users make available to modify their power profile. Indeed, the available capacity ($E^{f,u}_{av,var}$) to vary the power profile is determined as the difference between $SOC^{f,u}_{24}$, and the SOC under which it is not possible to modify the profile ($SOC_{min,var}$).

The flexibility availability of the single end-user profile $E^{f,u}_{av,var,h}$ is so determined by comparing the load profile of the single end-user and the ratio between $E^{f,u}_{av,var}$ and n_{def}.

The aggregation availability $E^{f}_{av,var,h}$ can be determined as the sum of the availability of the single end-user profiles.

$$E^{f,u}_{av,var} = \left(SOC^{f,u}_{24} - SOC_{min,var}\right)\cdot C^{u} \tag{25}$$

$$E^{f,u}_{av,var,h} = \min\left(E^{f,u}_{c,h}, \frac{E^{f,u}_{av,var}}{n_{def}}\right) \tag{26}$$

$$E^{f}_{av,var,h} = \sum_{u=1}^{n} E^{f,u}_{av,var,h} \tag{27}$$

After this step, DA can be considered concluded, so both $E^{f,u}_{grid,h}$ and $E^{f,u}_{av,var,h}$ are evaluated and can be communicated to the grid operator, representing the interface with the aggregator.

3.2. The Real-Time Algorithm (RTA) Step

The real-time step operation is illustrated in Figure 3.

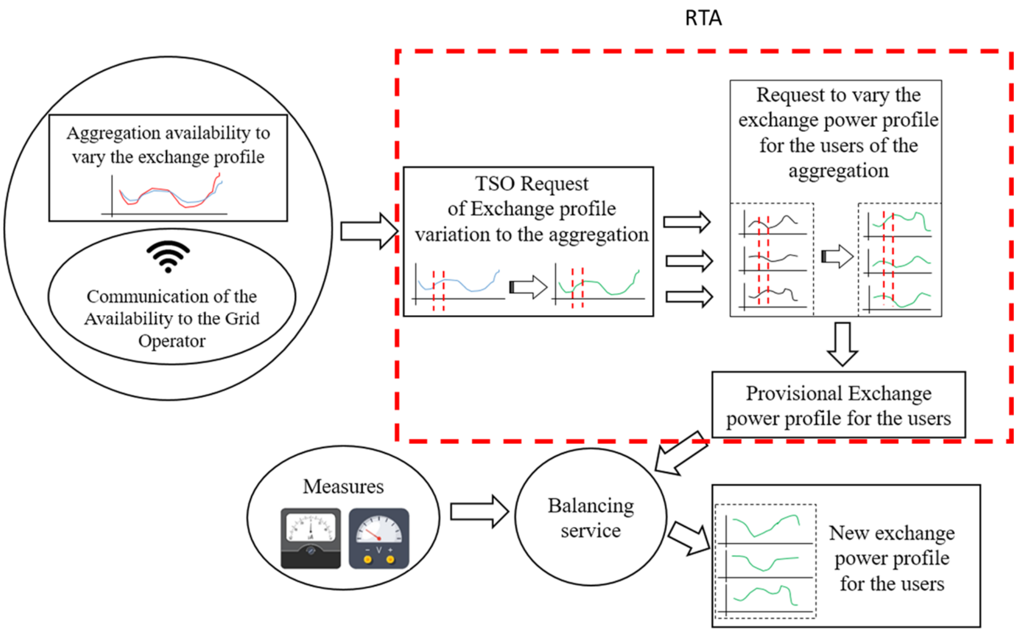

Figure 3. Real-time step flow chart.

The results of the DA are used to operate the real-time step (RT). Starting from $E^{f}_{av,var,h}$, the grid operator can send a flexibility request to the aggregation. Such a request, considering the end-users' flexibility and availability and the end-user distribution coefficients ($F^{u}_{d,var}$), is distributed among the n end-users. The new ESS and grid exchange power profiles ($E^{f,u}_{bat,h,var}$, $E^{f,u}_{grid,h,var}$) are so calculated for each end-user as follows:

$$F^{u}_{d,var} = \frac{E^{f,u}_{av,var}}{E^{f}_{av,var}} \quad (28)$$

$$E^{f,u}_{bat,h,var} = E^{f,u}_{bat,ch,h} - E^{f,u}_{bat,ds,h} - E^{f,u}_{av,var,h} \quad (29)$$

At the end of the process, there is a check to avoid overcharging (SOC > 100%) and overdischarging (less than SOC = 5%) of each ESS.

3.3. Balancing Step (BS)

The previous steps were performed using only the production and consumption forecasts as input. Therefore, it is possible that forecast errors occur, causing corresponding power imbalances and, consequently, significant imbalances in costs. For this issue, the balancing step becomes useful (Figure 4).

The BS considers, first of all, the configuration data (n, n_p, n_c, n_s) for the aggregation, the measured and forecasted grid power (P^{m}_{grid}, $P^{f}_{grid,h,var}$), the ESS energy ($E^{f,u}_{bat,h}$), the ESS capacity of the aggregation (C^{agg}). The SOC for the entire aggregation (SOC^{agg}) is determined as the weighted average of the end-users ESSs SOC, considering the capacity as an element to provide such weight. The applied criterion is to store the energy starting from the ESS that has a measured SOC less than the forecasted one and vice versa when a deficit of energy occurs, as described in [25]. First, it can be observed that for the end-users belonging to the aggregation, it is possible to significantly reduce imbalances, thanks also to self-dispatching.

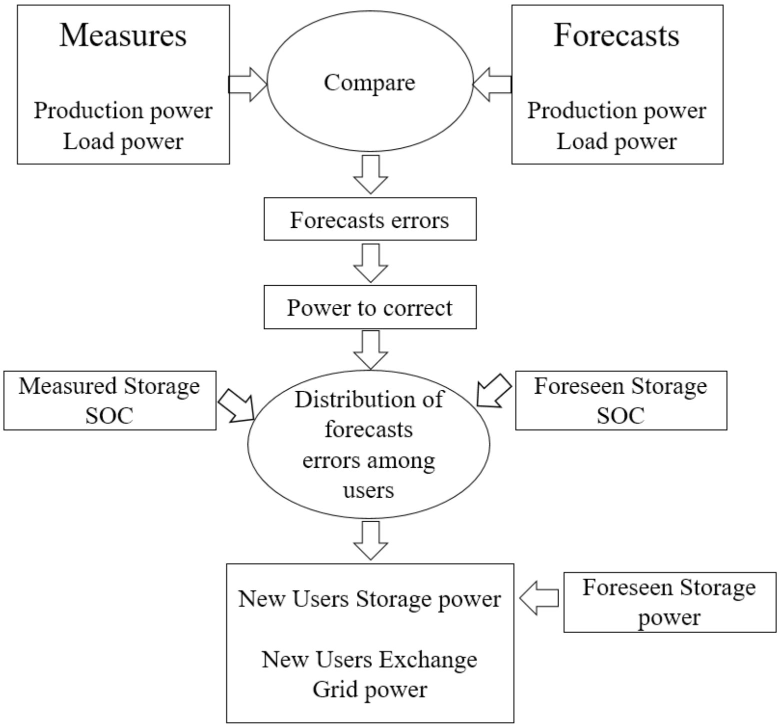

Figure 4. Balancing step flow chart.

In the balancing step, three main scenarios 'S' are analyzed:

- S1, where the power exchange with the grid is equal to the scheduled one (output of the DA step);
- S2, where the real grid exchange power profile is less than the scheduled one;
- S3, where the real grid exchange power profile is greater than the scheduled one.

In the case of S1, no operation is required; the schedule is operated.

In cases S2 and S3, it is necessary to operate to reduce as much as possible the error between the scheduled grid exchange power profile and the real one.

In the case of S2, two different events can occur: in the first event, the actual SOC^{agg} is greater than the forecasted value; in the second one, it is lower. In this second event, no correction is necessary because a possible operation of the ESS could invalidate the following time steps.

In the first event, instead, the variation in the power that the ESSs have to supply is determined (P^{agg}_{batt}).

$$P^{agg}_{batt} = P^{f}_{bat,h,var} + \min\left(\begin{array}{c} \left(P^{f}_{grid,h,var} - P^{m}_{grid}\right), \\ \left(SOC^{agg} - SOC^{f}_{h,var}\right) \cdot \frac{C^{agg}}{100} \end{array} \right) \tag{30}$$

where $P^{f}_{grid,h,var}$ and $P^{f}_{bat,h,var}$ are determined, respectively, from $E^{f,u}_{grid,h}$ and $E^{f,u}_{bat,h,var}$ considering the constant power during the hour; $SOC^{f}_{h,var}$ is the forecasted weighted average SOC for the ESSs of the aggregation.

Similarly, the BS can operate in S3. In this case, the SOC of the aggregation, SOC^{agg}, is evaluated: if it is equal to 100%, no operation is necessary; if it is less than 100%, the variation in the power that the ESSs have to supply is determined (P^{agg}_{batt}) as follows:

$$P^{agg}_{batt} = P^{f}_{bat,h,var} - \min\left(\begin{array}{c} \left(P^{m}_{grid} - P^{f}_{grid,h,var}\right), \\ \left(100 - SOC^{agg}\right) \cdot \frac{C^{agg}}{100} \end{array} \right) \tag{31}$$

At the end of the BS, the variation in the power that the ESSs have to supply P_{batt}^{agg} is distributed among the end-users of the aggregation. The power P_{batt}^{agg} can be distributed according to different criteria. The criteria used in the paper is to sort the end-user and distribute according to the difference between the real and the forecasted *SOC* in a proportional way, prioritizing the ESS that is less charged.

4. Case Study Description and Results

To test the proposed algorithm, a case study has been considered. It consists of 20 residential end-users located in the south of Italy, where 15 of them (from User A to User O) are provided with a PV plant, and 10 (from User A to User J) are also equipped with an ESS. The configuration of each end-user in terms of load, generation, and storage capacity is summarized in Table 1. The end-users are really monitored using a smart meter installed for each end-user.

Table 1. End-user configuration data.

End-Users	Load Contracted Power [kW]	Generation Contracted Power [kW]	Storage Capacity [kWh]
User A	3	3	5
User B	3	2	3
User C	4	3	6
User D	6	4	3
User E	3	3	6
User F	3	2	4
User G	3	3	3
User H	6	3	6
User I	10	6	12
User J	6	5	8
User K	3	3	-
User L	3	2	-
User M	15	10	-
User N	3	2	-
User O	6	3	-
User P	3	-	-
User Q	3	-	-
User R	6	-	-
User S	3	-	-
User T	15	-	-

The forecasted and instantaneous power data have been used for testing the algorithm, considering the month of March 2018.

4.1. DA Test Results

To carry out the test, the $SOC_{min,load}$ has been set to 50%, and the $SOC_{min,var}$ has been set to 15%.

First, to show how the algorithm operates, a single day is considered. The load and production aggregated power profiles are reported in Table 2. The energy surplus $E_{sur,d}^{f}$ is equal to 223.5 kWh, while the deficit $E_{def,d}^{f}$ is equal to 231.7 kWh.

Table 2. Aggregated load and production profile.

Time [h]	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24
E_c^f[kWh]	7.68	9.37	7.32	5.57	5.39	7.94	10.40	13.67	12.28	14.65	15.45	16.13	13.43	11.52	12.32	10.00	14.34	16.76	19.76	22.13	27.70	17.61	17.76	12.17
E_p^f[kWh]	0.00	0.00	0.00	0.00	0.00	0.00	0.36	9.08	23.85	34.47	41.37	44.06	45.66	41.67	35.74	24.37	10.61	1.88	0.00	0.00	0.00	0.00	0.00	0.00

The parameter $SOC_{24}^{f,u}$ is equal to 50% for each ESS of the aggregation. For the considered day, $E_{av,ch}^{f}$ is equal to 43.5 kWh, determined using Equation (8). In this case, $E_{av,ch}^{f}$ limits the power that can be stored because $E_{av,ch}^{f} < E_{sur,d}^{f}$.

The distribution coefficients F_d^u are determined (Table 3) and used to obtain $E_{av,ch}^{f,u}$. Therefore, the energy profiles that the ESSs can exchange to be charged and to supply the load are scheduled.

Table 3. The distribution coefficients and the ESS energy to store.

User	A	B	C	D	E	F	G	H	I	J
F_d^u [%]	9.2	12.6	10.3	6.9	12.6	8.0	6.9	10.3	12.6	10.3
$E_{av.ch}^{f.u}$ [kWh]	4	5.5	4.5	3	5.5	3.5	3	4.5	5.5	4.5

The forecast ESS energy profiles for every end-user are obtained (Figure 5). It is possible to observe that generally, the ESSs are charged in the first part of the day when a surplus exists, and they are discharged in the evening.

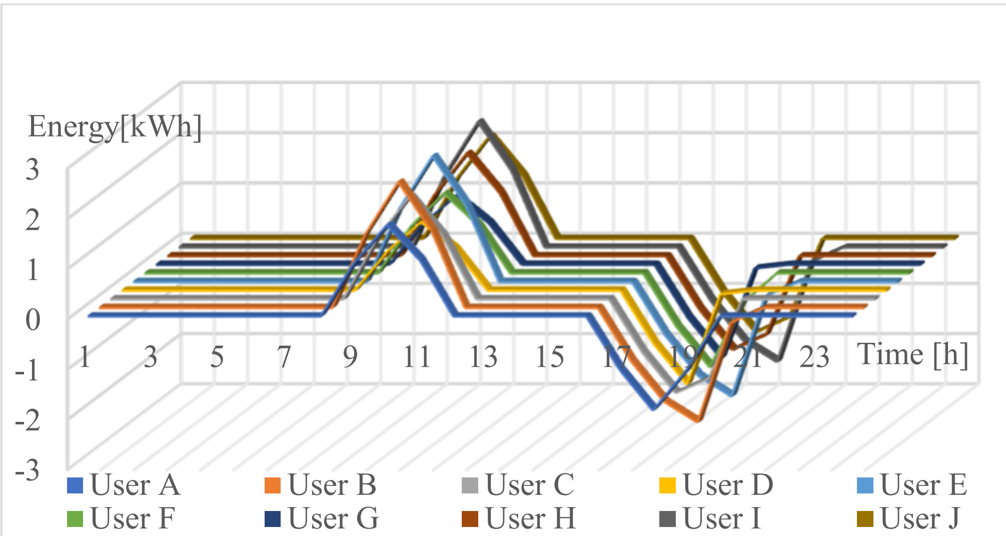

Figure 5. Day-ahead ESS forecasted profiles.

Once the day-ahead scheduling has been carried out, the availability of flexibility for the next day can be planned.

First $E_{av,var}^{f,u}$ is determined to obtain the hourly energy profile for each user $E_{av,var,h}^{f,u}$. Then, the availability to provide flexible services to the grid for the aggregation $E_{av,var,h}^{f}$ is determined using Equation (23). Such variables are reported in Tables 4 and 5. Starting from such results, it is possible to proceed with the RTA step. It is assumed that there are grid operator flexibility requests for the aggregation (see Table 6). These requests must be distributed among the end-users according to $E_{av,var}^{f,u}$. Then, using Equation (29), $E_{bat,h,var}^{f,u}$ is obtained (see Table 7).

Table 4. Overall flexibility and availability.

User	A	B	C	D	E	F	G	H	I	J
$E_{av.var}^{f.u}$ [kWh]	2.8	3.70	3.15	1.94	3.77	2.14	2.1	1.20	3.62	3.05

Table 5. Hourly aggregated flexibility and availability.

Hour	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24
$E^f_{av,var,h}$ [kWh]	1.86	1.65	1.63	1.72	1.61	1.59	1.61	1.82	0	0	0	0	0	0	0	0	1.65	1.65	1.73	1.90	1.72	1.73	1.74	1.89

Table 6. Grid operator flexibility requests.

Hour	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24
Flex Request [kWh]	1.85	0	0	1.72	0	0	1.61	0	0	0	0	0	0	0	0	0	0	1.64	0	0	0	1.72	1.73	1.88

Table 7. Real-time forecasted battery profile.

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24
A	−0.18	0	0	−0.18	0	0	−0.18	0	1.06	1.82	1.11	0	0	0	0	0	−1.06	−2.04	−1.07	0	0	−0.18	−0.18	−0.18
B	−0.24	0	0	−0.24	0	0	−0.22	0	1.46	2.51	1.53	0	0	0	0	0	−1.06	−2.08	−2.28	−0.29	0	−0.24	−0.24	−0.24
C	−0.20	0	0	−0.20	0	0	−0.20	0	1.20	2.05	1.25	0	0	0	0	0	−1.06	−2.07	−1.57	0	0	−0.20	−0.20	−0.20
D	−0.09	0	0	−0.10	0	0	−0.13	0	0.80	1.37	0.83	0	0	0	0	0	−1.06	−2.00	−0.07	0	0	−0.13	−0.13	−0.13
E	−0.24	0	0	−0.24	0	0	−0.17	0	1.46	2.51	1.53	0	0	0	0	0	−1.06	−2.11	−2.28	−0.29	0	−0.24	−0.24	−0.24
F	−0.15	0	0	−0.10	0	0	−0.11	0	0.93	1.59	0.97	0	0	0	0	0	−1.06	−2.02	−0.57	0	0	−0.15	−0.15	−0.15
G	−0.13	0	0	−0.13	0	0	−0.13	0	0.80	1.37	0.83	0	0	0	0	0	−1.06	−2.00	−0.07	0	0	−0.13	−0.13	−0.13
H	−0.20	0	0	−0.18	0	0	−0.04	0	1.20	2.05	1.25	0	0	0	0	0	−1.06	−1.90	−1.57	0	0	−0.02	−0.03	−0.18
I	−0.24	0	0	−0.19	0	0	−0.24	0	1.46	2.51	1.53	0	0	0	0	0	−1.06	−2.11	−2.28	−0.29	0	−0.24	−0.24	−0.24
J	−0.20	0	0	−0.16	0	0	−0.20	0	1.20	2.05	1.25	0	0	0	0	0	−1.06	−2.01	−1.57	0	0	−0.20	−0.20	−0.20

In Figure 6, for end-user A, the comparison between the ESS power profile scheduled (output of the DA step) and the ESS power profile evaluated in the RTA step is shown. The difference is limited, and the two profiles are comparable.

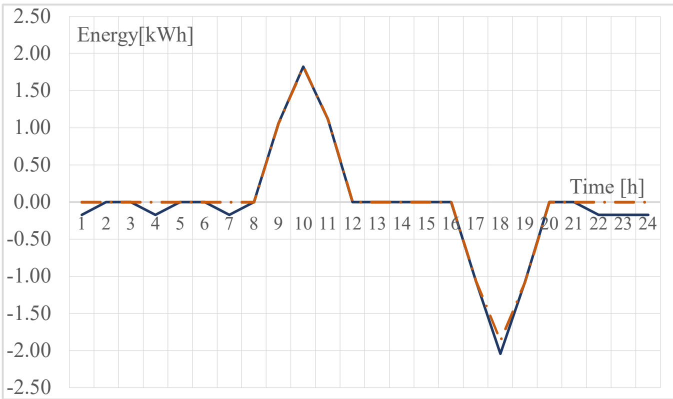

Figure 6. End-user A—comparison between the day-ahead ESS power profile (orange) and the real-time ESS power profile (blue) with a grid operator flexibility request.

In the end, the forecasts of the ESSs SOC are determined; their variation depends only on possible forecasting errors.

4.2. BS Results

At the end of the RTA, the BS starts. Firstly, it compares the hourly production and consumption forecasts with the measures (real power values) every 10 min. Starting from the results of DA, the $SOC^{f,agg}_{h,var}$ and the SOC^{agg} must be determined.

If an error between the forecasted and measured power occurs, it is necessary to verify if such error can be covered by the ESSs.

When an excess of power exists, the BS operates with the aim of storing the excess energy as far as possible, as expressed in Equation (27), while when a deficit occurs, Equation (26) is used.

Once the contribution to the balancing step has been determined, it will be possible to calculate the power that the ESSs have to exchange after such a correction. Thanks to the balancing step, it is possible to significantly reduce the imbalances. Based on the accuracy of the forecasts and the type of day, it is possible to cover more than 60% of the imbalances that would have occurred if the algorithm had not been used.

4.3. Long-Term Performance Analysis

After the results for a single day have been presented to understand the operation of the algorithm, an overall analysis of the results for the considered month is carried out.

The results are discussed, considering three cases:

- Case A, which is the base case described before;
- Case B, where $SOC_{min,load}$ is decreased to 40%;
- Case C, where the capacity of the ESSs is increased (50% more than the base case).

4.3.1. Case A

For the considered period, the energy surplus obtained for the entire aggregation is equal to 3629 kWh, while the energy deficit is equal to 6328 kWh.

In the first step of the algorithm, in the day ahead, the energy surplus adsorbed by the ESSs is equal to 1373 kWh, while the energy supplied by the ESSs is equal to 1110 kWh.

The energy stored in the ESSs is about equal to 30% of the aggregation energy surplus; this is due to the limit of the overall ESS capacity and to the possibility of scheduling the ESS in this step until a deep of discharge (DoD) of 50% to supply the load.

On the other hand, the overall availability provided to carry out flexibility services to the grid is equal to 600 kWh, while the grid operator flexibility services actually requested and supplied (unless forecast errors) are equal to 227 kWh, which is 38% of the communicated availability for flexibility services (Figure 7).

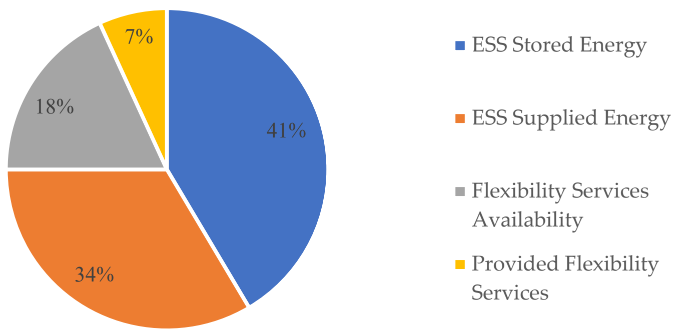

Figure 7. Use of stored energy in supplying loads and providing services—Case A.

In summary, the energy used to carry out services to the grid is about 16.5% of the stored energy surplus; the remaining part, about 83.5%, is scheduled to supply the loads.

Such values obviously depend both on the overall capacity of the ESSs and on the limits imposed on the possibility of being able to discharge the storage system under the defined DoD.

4.3.2. Case B

If $SOC_{min,load}$ is decreased (setting it equal to 40%), it can be observed that the energy surplus absorbed in this case by the ESSs is equal to 1512 kWh, while that supplied to the loads is equal to 1318 kWh. The energy stored is approximately equal to 42% of the energy surplus from the aggregation. On the other hand, an overall availability to carry out grid operator flexibility services equal to 433 kWh is provided, while the services requested and provided (unless forecast errors) are equal to 165 kWh, equal to 38% of the availability, which is similar to the previous case (Figure 8). In this case, only 10% of the stored energy surplus is used to provide flexibility.

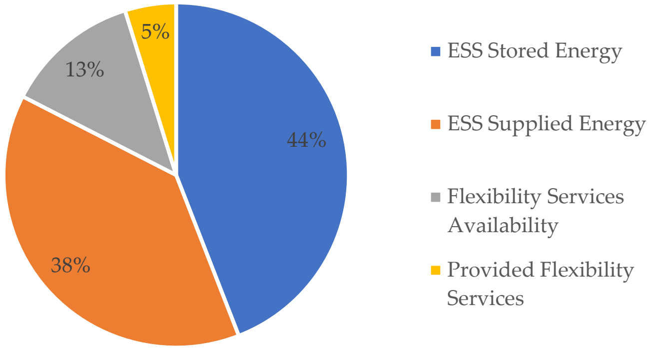

Figure 8. Use of stored energy in supplying loads and providing services—Case B.

It is possible to observe that after changing $SOC_{min,load}$, the energy stored and discharged from the ESSs (supplying the load and providing flexibility services) is greater, compared to the previous case.

4.3.3. Case C

The overall capacity of the ESSs is increased to 50% while maintaining the $SOC_{min,load}$ equal to 50%. The energy surplus absorbed in this case by the ESSs is equal to 1926 kWh, while the supplied energy is equal to 1547 kWh. The energy stored in the ESSs is equal to 53% of the surplus of the aggregation (Figure 9).

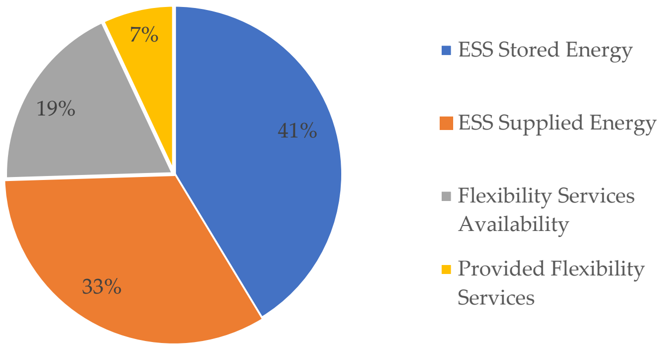

Figure 9. Use of stored energy in supplying loads and providing services—Case C.

The overall availability to provide grid operator flexibility services is equal to 861 kWh, while the services requested and provided (except for forecast errors) are equal to 325 kWh, or approximately 38% of the available resources.

4.3.4. Summary

To obtain a complete picture, the results obtained in the three different cases are summarized below (Table 8).

Table 8. Long-term analysis performance.

	Case A **Base Case**	**Case B** $SOC_{min,load}$ **= 40%**	**Case C** **ESSs Capacity Increased**
ESSs Stored Energy	1373 kWh	1512 kW	1926 kWh
ESSs Supplied energy	1110 kWh	1318 kWh	1547 kWh
Flexibility Services Availability	600 kWh	433 kWh	861 kWh
Provided Flexibility Services	227 kWh	165 kWh	325 kWh

Starting from the base case, it is possible to observe how the possibility to supply the loads until a SOC of 40% (CASE B) allows both to supply and store more energy with the

ESSs; naturally, it also increases the ESSs capacity, but not proportionally. On the contrary, reducing the minimum SOC to supply the loads to 40% does not allow for more flexibility services, while increasing the ESS capacity makes it possible to increase the amount of energy for flexibility services.

To find a better solution to maximize both energy used to supply the loads and to provide services to the grid, it becomes necessary to combine the correct parameters used, depending on the PV production and the loads.

5. Conclusions

In this paper, an algorithm to opportunely manage the energy flows inside an aggregation operating following the Power Cloud concept has been presented. In this framework, different kinds of users (prosumers, consumers, and prosumages) connected via a public distribution network are aggregated. The main objective was to verify the possibilities of exploiting the flexibility of behind-the-meter technologies integrating "all-in-one" photovoltaic plants, storage systems, and other technological solutions in order to maximize benefits to end-users.

The algorithm schedules the energy that the end-user ESSs must exchange inside the aggregation to maximize the use of renewable sources, provide grid flexibility services, and simultaneously provide balancing services. The algorithm is organized into three different steps: the day-ahead step, the real-time step, and the balancing one.

The first step determines the charge/discharge of storage systems present in the aggregation to maximize renewable energy self-consumption using forecasted hourly production and consumption. A reference power profile is determined to exchange with the grid.

The second one determines in real-time how to modify that profile if flexibility services are required by the TSO or DSO, and the third one compensates for errors in forecasting production and/or consumption.

A test has been implemented to illustrate a real aggregation of 20 end-users, demonstrating the effectiveness of the proposed algorithm in reducing by about 60% the power imbalances that can occur if forecast errors and/or grid flexibility requests exist.

One of the principal characteristics of the proposed algorithm to be highlighted is that it can manage the charge/discharge phases of the ESSs present on the user side in a blind manner for the final user. So, an adequate level of aggregate self-consumption and the ancillary services required by the power system operator are met without any change in user habits. The energy storage systems are used to increase self-consumption and provide real-time grid operator flexibility services.

The main drawback of the proposed algorithm is related to considering some variables (especially power) as deterministic ones while some kind of uncertainty exists, especially in the day-ahead step.

In the future work of the authors, (i) the above-mentioned uncertainty will be considered in order to avoid errors deriving from deterministic assumptions; (ii) a possible improvement in the benefit of the proposed algorithm will be investigated considering the use of an opportune ICT platform, respecting the concept of Power Cloud, able to exchange data among aggregators and end-users in order to increase the end-users advantage from self-consumption and flexibility services delivered to the system without changing their power consumption behavior and habits.

Author Contributions: Conceptualization, P.V.; methodology, P.V., N.S. and A.P.; software, D.M. and P.V.; validation, A.P. and G.B.; formal analysis, A.P. and N.S.; investigation, P.V. and D.M.; resources, N.S.; data curation, G.B.; writing—original draft preparation, P.V.; writing—review and editing, A.P., G.B. and N.S.; visualization, P.V. and D.M.; supervision, A.P.; project administration, N.S.; funding acquisition, D.M. and A.P. All authors have read and agreed to the published version of the manuscript.

Funding: This work was financed by the Italian Ministry of Economic Development (MISE) and the Ministry of Education, University and Research (MIUR) through the National Operational Program for Business and Competitiveness 2014–2020, PON F/050159/01-03/X32, and by the European Union's Horizon 2020 research and innovation program under grant agreement n° 864283.

Data Availability Statement: Not applicable.

Conflicts of Interest: The authors declare no conflict of interest.

Abbreviations

EV	Electric vehicle	$E^{f,u}_{def,d}$	Aggregated daily energy deficit
EC	Energy Community	$E^{f}_{def,d}$	Aggregated daily energy deficit
ESS	Energy storage System	$E^{f}_{sur,h}$	Aggregated hourly energy surplus
P2P	Peer-to-peer	$E^{f,u}_{bat,ch,h}$	Charging Energy profile for the ESS
LEC	Local energy community	$E^{f,u}_{crg,d}$	Energy that each user has to store daily
ANN	Artificial neural network	F^{u}_{d}	Surplus distribution factor
SOC	State of charge	$E^{f,u}_{crg,d,res}$	Daily residual energy that each user has to store
DAA	Day-ahead algorithm	$E^{f,u}_{bat,ds,h}$	Hourly energy that the user equipped with ESS has to supply
RTA	Real-time algorithm	$E^{f,u}_{dis,res,h}$	Hourly residual energy in the ESS is useful to supply the load
TSO	Transmission system operator	$SOC_{min,load}$	SOC under that the ESS discharge cannot be scheduled
n_p	Number of producers	$E^{f,u}_{grid,h}$	Hourly profile to be exchanged with the grid (baseline)
n_c	Number of consumers	$E^{f,u}_{av,var}$	Daily available capacity to vary the profile
n_s	Number of end-users equipped with ESS	$SOC_{min,var}$	SOC, under which it is not possible to modify the profile
$E^{f,u}_{p,h}$	Hourly production forecasts for each user	$E^{f,u}_{av,var,h}$	Hourly flexibility availability of the single end-user
$E^{f,u}_{c,h}$	Hourly load forecasts for each user	n_{def}	Number of hours where a deficit exists
$E^{f}_{c,h}$	Aggregated hourly consumption forecast	$E^{f}_{av,var,h}$	End-users aggregation availability
$E^{f}_{p,h}$	Aggregated hourly production forecast	$F^{u}_{d,var}$	User availability and the distribution factor
$E^{f,u}_{ex,h}$	Exchange power profile with the grid for each user	$E^{f,u}_{bat,h,var}$	New ESS power profiles
$E^{f}_{ex,h}$	Aggregated exchange power profile with the grid	$E^{f,u}_{grid,h,var}$	New grid power profiles
$SoC^{f,u}_{24}$	SOC forecast for the last hour of the day before	C^{agg}	Aggregated ESS capacity
$E^{f,u}_{av,ch}$	Energy that can be stored in the ESSs for each user	SOC^{agg}	SOC for the entire aggregation
$E^{f}_{av,ch}$	Aggregated energy that can be stored in the ESSs	P^{m}_{grid}	Measured grid power
C^{u}	Capacity for each ESS	$P^{f}_{grid,h,var}$	Forecasted grid power
$E^{f,u}_{sur,h}$	Hourly energy surplus for each user	P^{agg}_{batt}	Aggregated power variation that ESSs have to supply
$E^{f,u}_{def,h}$	Hourly energy deficit for each user	$P^{f}_{bat,h,var}$	Forecasted ESS power
$E^{f,u}_{sur,d}$	Daily energy surplus for each user	$SOC^{f,agg}_{h,var}$	Forecasted weighted average SOC for aggregation ESSs
$E^{f}_{sur,d}$	Aggregated daily energy surplus	V2G	Vehicle to Grid

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