Scaling-up Power Flexible Communities business models empowered by Blockchain and AI

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Nomenclature

aFRR	Automatic Frequency Restoration Reserve
APL	Ancillary Process Loads
BM	Balancing Markets
BSP	Balancing Service Providers
BRP	Balancing Responsible Party
CHP	Combined Heat and Power
CM	Community Manager
DAM	Day-ahead Market
DER	Distributed Energy Resources
DR	Demand Response
DSO	Distribution System Operator
EBGL	Electricity Balancing Guideline
EC	Energy Community
EMS	Energy Management System
EPL	Environmental Process Loads
EU	European Union
FAT	Full Activation Time
FCR	Frequency Containment Reserve
FRR	Frequency Restoration Reserve
HVAC	Heating, Ventilation, and Air Conditioning
IDM	Intraday Market
LFC	Load-Frequency Control
mFRR	Manual Frequency Reserve
MPL	Main Process Load
MO	Market Operator
REC	Renewable Energy Community
TCL	Thermostatically Controlled Load
TSO	Transmission System Operator
RR	Restoration Reserve
USEF	Universal Smart Energy Framework
VPP	Virtual Power Plant

Executive Summary

To meet the 55 percent GHGs reductions target by 2030, set by EU's latest mammoth climate emergency Fit for 55 package [1], there is a pressing need to significantly reduce our energy consumption, and switch to clean and renewable energy sources (i.e, solar and wind energy) for what we must consume.

In this context, electrification of end uses (i.e.: heating, cooling, transportation etc.) and the decarbonization of electricity supply with clean and renewable energy sources (i.e.: solar and wind energy) are widely recognized to be among the best strategies to achieve these energy consumption reductions and decarbonization goals. However, implementing these strategies will turn the existing electricity system upside down requiring higher levels of demand-side flexibility to efficiently operate and control the electricity system of the future. On the other hand, if executed well, both these strategies can bring plenty of system-wide benefits to the entire electricity system. For instance, active electricity network management could leverage demand-side flexibility of newly introduced distributed electricity assets (i.e.: battery storages, domestic appliances, electric vehicles, heat pumps and HVAC systems etc.) in alleviating network constraints associated with the integration of variable generation of intermittent renewables sources in the power network [2].

Creation of energy communities in "Clean Energy for All Europeans Package" should enable energy community members (i.e.: prosumers and consumers) to provide part of the needed demand-side flexibility for actively maintaining the real-time power balance of the European electricity grids, but in practice these energy community members (i.e.: prosumers and consumers) cannot yet access all the existing ancillary and flexibility markets directly because they still face many technical, economical, and legal challenges. The biggest of all hurdles for individual energy community members (i.e.: prosumers and consumers) are to be able to meet the minimum bid volume required to participate in these markets. Therefore, to enable this type of energy community members (i.e.: prosumers and consumers) to access the ancillary and flexibility markets, the aggregation of demand-side flexibility and excess PV generation of these energy community members (i.e.: prosumers and consumers) managed by the figure of an aggregator or energy community that represents a group or community of end-users, is a crucial first step. Additionally, new market players such as aggregators, energy service companies, and energy communities can also remove other technical, economical, and legal bottlenecks for individual energy community members (i.e.: prosumers and consumers) and help them in fully valorizing their demand-side flexibility and excess PV generation on all existing and emerging local and upstream electricity markets by optimizing and controlling their energy demands (e.g., the flexible ones) and generations [3] [4].

To facilitate this valorization process, FleXunity project is to develop an integrated platform for managing and optimizing the demand-side flexibility and excess PV generation resources of energy community members (i.e.: prosumers and consumers) by leveraging a virtual power plant configuration. Such a platform could be used by new market players such as aggregators, energy service companies, and energy communities (in particular, community managers – CMs). FleXunity also aims to develop and validate new business models (prosumer P2P, retailer/ aggregator, TSO flex procurement, as shown in Table 1**). These business models will be discussed in greater detail in "D3.3-New EC Business Models implementation" of FleXunity project.**

Table 1 - Business Models to be validated in the FleXunity project

Business Models	
End–User Level	Sharing surplus local energy within the Energy Community.
	Prosumer value via optimal demand side and DER management.
Retailer/Aggregator Level	Aggregation of the flexible loads as universal VPP / CM.
	Retailer accessing local energy market for portfolio optimization.
TSO Level	TSO Balancing services using aggregator flexibility.

Furthermore, the workflow in Figure 1 summarizes the FleXunity optimization approach. The key data inputs for the optimization process such as forecasted energy prices, forecasted energy generation, forecasted energy demand, and generic operational models for different categories of flexible energy appliances (Table 2) have been discussed in "Input Data for FleXunity Optimization Model". The outcome of such an optimization process would be day ahead scheduling of all appliances belonging to the consumers/prosumers, i.e., the energy needed/generated at each hour of the day. Having the scheduling optimization finished and knowing the day ahead loads at each hour, it is possible to identify which loads are the controllable ones. The controllable loads can, therefore, be traded in existing ancillary and flexibility markets.

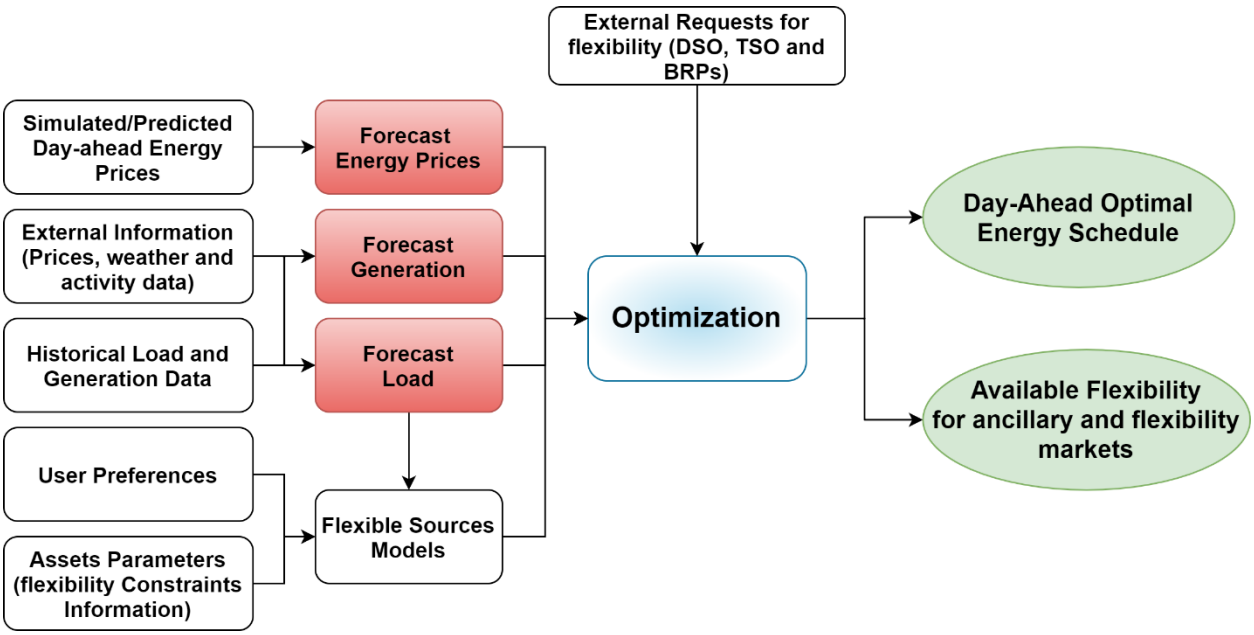

Figure 1 Workflow for an optimization algorithm for an Energy Community

Table 2 - Classification of Controllable Flexible Assets.

Flexible Community Energy Assets	
Curtailable Appliances (CCA)	**CCA** are the appliances whose energy consumption can be curtailed in response to the energy price or system request, e.g., lightning systems.
Uninterruptible Appliances (CUA)	**(CUA)** are devices that must run through a complete set of operations before being turned off, e.g., washing machines, clothes dryers and dishwashers must run for a complete program when started.
Thermostatically Controlled Appliances (C-TCA)	**(C-TCA)** are the category of the appliances with thermal storage capacity which helps the possibility to shift or anticipate load. e.g., ambient heating/cooling systems, electric water heaters and refrigerators.
Energy Storage Systems (ESS)	**(ESS)** are supposed to store energy in low-cost times to discharge in high-cost times to create value for the available energy storage capacity, e.g., Electric Vehicle (EV) and Battery Storage.

1. Introduction

Recently, the European Union (EU)'s "Fit for 55" package has increased the EU's renewable energy deployment target for 2030 from the current 32 percent to as high as 40 percent [1]. To hit this goal by 2030, the EU must accelerate the pace of renewable energy installations' deployment.

While the large-scale integration of intermittent renewable sources (i.e, solar and wind energy) is essential to the electricity system [5], several challenges stand in its way. Firstly, electricity production from these sources fluctuates. Secondly, it is difficult to predict the fluctuations in electricity production from these sources. Traditionally, power systems never had to deal with such challenges. Therefore, existing frameworks to monitor, control, and optimize the large-scale conventional energy generation units are quickly becoming obsolete [6] leading to challenges in planning and controlling the energy production, transmission, and distribution activities in the power system [7].

Flexible and responsive power systems are the "antidote" for dealing with complexities and uncertainties associated with integration of clean and renewable energy technologies in the electricity system. The current electricity systems do not possess the flexibility needed in realizing a clean and renewable energy future, which if not tackled, could lead to substantial curtailment of renewable energy sources and/or increased generation from conventional generating units and skyrocketing network costs [8].

1.1. A New Energy Paradigm

Maintaining the real-time power balance of the electricity grid in this new energy reality would not be possible without a paradigm shift, in which demand on the system matches the supply of energy in real-time, which is contrary to the system's original design, in which large-scale generation matched the energy demand at all times [2]. This paradigm shift is finally possible because of the development of smart grid solutions such as distributed energy resources management system (DERMS) [6]. These technological advancements are finally enabling demand side to access various avenues for monetization, similar to those of generation through BRP [8]. Distributed electricity consuming and generating devices (i.e., battery storage, distributed generation, domestic appliances, electric vehicles, heat pumps, HVAC systems, etc.) have already started providing flexibility to the system by adjusting their consumption and production automatically, in response to external signals (i.e., implicit price signals or explicit control signals) to maintain the real-time power balance of the electricity grid. Traditionally, this type of flexible demand response has been provided by the commercial and industrial (C&I) sector, through control of large technical equipment, processes, and stand-by generation [9]. Involvement of the residential sector was lagging due to the small number and widely distributed nature of flexible resources. However, the electrification of private transportation and heating are gradually changing this, and it is anticipated that in the near future, a large chunk of individual consumers/prosumers will be able to provide part of the needed demand-side flexibility to maintain the real-time power balance of the electricity grid.

Besides, optimizing and exploiting the individual consumers/prosumers electric flexibility potential in response to external signals not only provides end-users with an additional revenue and an opportunity to lower their energy costs, but also enables system operators (DSOs and TSOs) to alleviate, at local level, network constraints associated with variable generation and introduction of new electric loads [3]. Individually these consumers/prosumers and their assets might not be able to provide significant flexibility

to the system, but when the contributions from very large numbers (e.g. hundreds or thousands) of such customers are aggregated, there could be potentially hundreds of MW of load gain/reduction as an alternative to expensive grid reinforcements. At EU level, avoided investments at distribution level could reach €5 billion per year up to 2030 [5]. Therefore, it is widely recognized that optimizing and exploiting the full potential of electrical flexibility of hundreds of thousands of residential consumers/prosumers could maximize the welfare of all relevant stakeholders in the energy value chain, including residential consumers/prosumers, system operators (DSOs and TSOs), and market operators [3].

1.2. The Clean Energy for All Europeans package

Although demand-side flexibility has an essential role to play in the planning and operations of the future energy systems, demand side still lacks a level playing field in almost all existing local and upstream electricity markets, when compared to the supply side. That is because traditionally, electricity markets around the globe and particularly in the EU, have been developed with the role in mind of the supply side (i.e., the role of electricity generation) as exclusive resource for maintaining the real-time power balance of the electricity grid. However, technological advances in the field of smart metering, as well as the need for flexibility to alleviate network constraints associated with the integration of variable generation sources on the system, have changed the tide towards the role which the demand side – namely electricity end-users and their agents – can play in the efficient functioning of the emerging local and upstream electricity markets [8].

The EU understands that there is a need to take leaps, not steps, to keep up with the new energy reality. Its “Clean Energy for All Europeans” policy package (henceforth called simply “Clean Energy package”) represents one such leap, designed to accelerate the clean energy transition. With this package, the EU aims to put consumers at the heart of the energy transition, giving every European citizen owning distributed electricity consuming and generating devices a clear right to consume, store or trade their generated energy and valorize their electrical flexibility potential in all existing and emerging local and upstream electricity markets, alongside traditional market actors in a non-discriminatory manner [10]. The Clean Energy package also enables active consumers to group with other likeminded energy customers, collectively forming energy communities; Citizen Energy Communities (CECs) and Renewable Energy Communities (RECs) as formally recognized in the Clean Energy package, can exercise similar activities in all existing and emerging local and upstream electricity markets, alongside traditional market actors in a non-discriminatory manner [11].

The following are the main legislative files of The Clean Energy package:

- Energy Performance of Buildings Directive (EU) 2018/844;
- Renewable Energy Directive (EU) 2018/2001;
- Energy Efficiency Directive (EU) 2018/2002;
- Governance of the Energy Union and Climate Action Regulation (EU) 2018/1999;
- Electricity Regulation (EU) 2019/943;
- Electricity Directive (EU) 2019/944;
- Regulation on Risk-Preparedness in the Electricity Sector (EU) 2019/941, and

- Regulation on the European Union Agency for the Cooperation of Energy Regulators (EU) 2019/942.

Despite consumer-centric energy policy initiatives, such as the Clean Energy package, being already in place, in many European states, individual consumers/prosumers cannot yet access all existing local and upstream electricity markets directly, because they still face varied technical, economical, and legal challenges. One of the biggest hurdles faced by individual consumers/prosumers is the high minimum bids required for participating in these markets (usually in the order of MWs). Such bids remain high because it is difficult for Market and System Operators to deal with many end-users individually and concurrently single consumers/prosumers might find it difficult and discouraging to deal directly with a market.

In this context, the figure of an aggregating entity that represents a group or community of end-users in a market has the potential to solve the problems faced by both parts. Accordingly, aggregators or energy community managers can combine excess PV generation and flexibility of individual consumers and/or prosumers and exploit it in existing and emerging local and upstream electricity markets. In doing so, the Market Operators and System Operators would only have to qualify and manage one additional market participant; on the other hand, the aggregator should be able to engage end-users, offering easy-to-understand contracts and managing technical issues as needed [3].

1.3. Project Goal

The main goal of the FleXunity project is to develop an integrated platform for managing and optimizing the demand-side flexibility and excess PV generation resources of energy community members (i.e.: prosumers and consumers) by leveraging a virtual power plant configuration. Such a platform could be used by new market players such as aggregators, energy service companies, and energy communities (in particular, community managers – CMs). FleXunity also aims to develop and validate new business models (prosumer P2P, retailer/ aggregator, TSO flex procurement, as shown in Table 1). These business models will be discussed in greater detail in "D3.3-New EC Business Models implementation" of FleXunity project.

Table 3 - FleXunity Targeted Flexibility Services.

FleXunity Targeted Flexibility Services	
Balancing and Ancillary Services (TSO)	aFRR (or equivalent), for frequency regulation
	mFRR (or equivalent), for frequency regulation and congestion management
	RR, for frequency regulation and congestion management
Services for Distribution Network Management (DSO)	Load shifting, for voltage control
	Other specific local product available for supporting congestion management.

In addition to energy community optimization, FleXunity platform will test the provision of flexibility for balancing and ancillary services (as shown in Table 3) by energy Communities´ distributed energy assets (i.e.: distributed generation, battery storages, domestic appliances, electric vehicles, heat pumps and HVAC systems etc.) as explained in "D4.1 –TSO balancing markets requirements for EC flexibility services" of FleXunity project.

1.4. Deliverable Purpose and objectives

The main goal of this task is to develop advanced Artificial Intelligence-based optimization algorithms to optimize and control the operation of Energy Communities´ distributed energy assets (i.e., distributed generation, battery storage units, domestic appliances, electric vehicles, heat pumps and HVAC systems etc.) in response to foreseen electricity prices on the wholesale market – encouraging energy use at off-peak hours with low prices and discouraging energy use at peak hours with high prices. First and foremost, optimized operations' scheduling of energy demands (e.g., the flexible ones) and generation in response to time-of-use and dynamic pricing can reduce the energy bills for consumers/prosumers. Additionally, this strategy could improve the integration of renewable energy sources because dynamic price signals are heavily influenced by renewable energy sources production in the energy system. Assuming that the electricity market mechanisms are functioning well, high renewable energy sources production shall lead to lower electricity prices. Therefore, matching energy use with lower electricity prices on wholesale market could help and improve RES integration in the energy system [12].

Optimization of Energy Communities´ distributed energy assets would take place in three levels:

Optimization Levels	
1) Self-Optimization	Firstly, optimization of each individual prosumer is performed in accordance with the customer predefined goals (i.e.: higher self-consumption from Solar PV or scheduling operations to match low wholesale prices hours).
2) Community Optimization	Secondly, optimization of the community assets is performed in accordance with the community predefined goals. (i.e.: to optimize self-consumption for community by sharing surplus local energy within the Energy Community).
3) Market-based Optimization	Thirdly, when consumers/prosumers and community have got some surplus energy and extra electrical flexibility and do not need it locally then this excess energy and extra electrical flexibility can be valorized on existing and emerging local and upstream electricity markets generating additional revenue streams for consumers/prosumers.

The approach behind FleXunity is to use real-time data, individual energy demand forecasts, individual energy generation forecasts (e.g., PV), market prices, and local constraints, and the possibility to shift electricity demand using the flexible assets (e.g., water heater) and the controllable batteries, if available, to best schedule the community's bid to the wholesale electricity markets (day-ahead, intra-day). In addition to the wholesale electricity market, the community would try to sell its remaining electrical flexibility on balancing and ancillary service markets (FCR, aFRR, mFRR), and local flexibility markets (voltage / reactive power control and congestion management) and get extra remuneration for the community participants. As described in [3], the optimization uses the same flexible assets that can be traded in an ancillary/flexibility market, therefore, a negative competition must be avoided. For this reason, it is considered that the available (extra) flexibility will be calculated taking into consideration the results of the energy optimization algorithm.

1.5. Report structure

The rest of this document is organized as follows: Chapter 2 contains the problem description and possible solution approach. Chapter 3 describes the different flexibility solutions and business model levels (prosumer P2P, retailer/ aggregator, and TSO flexibility procurement) that FleXunity project aims to develop and validate with the FleXunity Platform. Chapter 4 describes operational models of flexible assets that would be used in the optimization process, to make operational decision of Community energy assets. Chapter 5 describes the FleXunity Optimization Model and the necessary data sources to solve the optimization problem, also highlighting issues and impacts of uncertainties in input data sources on the decision process. The mathematical model formulations used on the software algorithms are given in Chapter 6. Lastly, conclusions and references are provided.

2. FleXunity Problem description

2.1. A Representative Example

This section presents an illustrative example of application of the optimization problem addressed in this deliverable:

Consider an energy community of prosumers and consumers with the following resources:

- Local Generation (i.e.: Solar PV);
- A set of controllable flexible loads (i.e., shiftable, and curtailable etc.);
- Battery Storage System;
- EV Charging Points (i.e.: Vehicle to Grid – V2G – technology);
- A main meter that meters the net exchange with the grid (i.e.: the purchase and the sales);
- Smart meter to collect Solar PV generation data;
- Smart meter to collect information about the EV charging points and the battery storage;
- Smart power plugs to monitor and control the connected flexible loads.

There could be two types of electricity end-users in the energy community. The prosumers who can consume and produce electricity and the consumers that are only able to consume electricity (Figure 2).

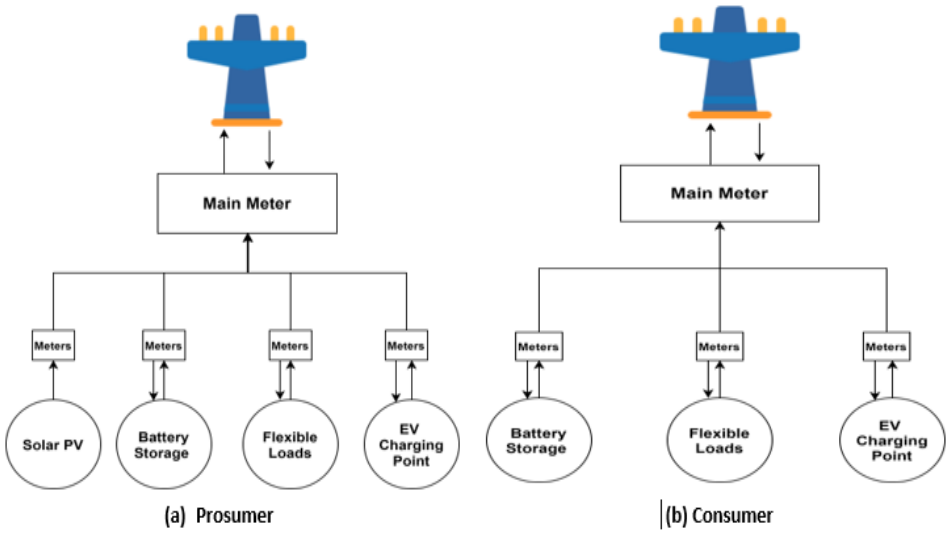

Figure 2 Energy community members (i.e prosumers and consumers) with resources

2.1.1. Flexible Resources

In the provided example case, energy community members (i.e prosumers and consumers) may own the following flexible resources:

- **Controllable Flexible loads**
  - Controllable Curtailable Appliances (CCA): Curtailable appliances are those whose consumption can be curtailed in response to high electricity prices or requests from the system operator. CCA can be specific lighting systems, electric heaters without thermostat, water pumps or any other appliance that can be controlled and about which the consumer/prosumer is not bothered (in terms of being off for short periods).
  - Controllable Uninterruptible Appliances (CUA): The CUA are generally wet appliances, i.e., washing machine and dishwasher, and can be considered uninterruptible demands whose use can be shifted to time-frames associated with low electricity price. They are considered uninterruptible loads because they must run throughout a complete cycle of operations before being turned off or they will not delivery their specific service, e.g., if the washing machine is turned off after the rising stage, the clothes will be clean, but extremely wet.
  - Controllable Thermostatically Controlled Appliances (C-TCA): The C-TCA have thermal storage capability which helps the possibility to shift or anticipate load. Such devices work as an energy buffer, enabling some energy storage during low-price hours to supply the heating needs during the high-price hours. The flexibility provided by the thermal storage will directly depend on the comfort conditions that will be defined/required by each prosumer/consumer.
- **Battery Storage:** Battery Storage is generally used to enable the disconnection from the grid and provide local energy balance or to reduce costs by charging on low energy prices and selling/using energy on high prices (also known as energy arbitrage).
- **EV Charging Point with V2G Technology**: Like battery storage, EV charging and discharging can be planned in such a way that the total costs are minimized.

As stated above, some of the energy assets owned by energy community members (i.e.: prosumers and consumers) can be controllable, which means that their consumption and production patterns can be modified. As a result, these flexible and controllable energy assets have the possibility to provide flexibility, commonly referred in the published literature as the modification of generation injection and/or consumption patterns in response to external signals (i.e., implicit price signals or explicit activation signals) to deliver a flexibility service within the electrical system [13].

2.1.2. Main Assumptions for FleXunity optimization approach

Moreover, assume that energy community members (i.e.: prosumers and consumers) hold a Time-Of-Use (ToU) contract with their electricity supplier/retailer, according to that contract electricity prices differ hour by hour (ToU) as per prices at the wholesale electricity markets (day-ahead market).

Additionally, assume that energy community members (i.e.: prosumers and consumers) have signed some contract with grid operator for kWmax, which binds electricity end-users to pay double the ToU price for every kW they consume exceeding kWmax.

Furthermore, assume that when the prosumer injects the excess electricity back to the grid, he/she gets only half of the ToU price. In many countries, excess electricity injection back to the grid is remunerated quite low, to discourage too much solar feeding into the grid, which creates instability in distribution grids.

Finally, assume that besides energy community members (i.e.: prosumers and consumers) self-consuming and sharing their flexibility and excess PV generation within the energy community. Energy community members (i.e.: prosumers and consumers) have a contract with aggregator or Community Manager (CM) to sell their services (flexibility and exceeding PV generation) to the stakeholders as TSO, DSO and BRP (Balancing Responsible Parties). To provide this type of services (flexibility and exceeding PV generation) to the stakeholders as TSO, DSO and BRP, the aggregator/CM aggregates the flexibility and excess PV generation of participants in an energy community as consumers and prosumers.

The Time-Of-Use (ToU) contract with varying electricity prices, the kWmax contract which penalizes the electricity purchase exceeding certain kW limit, very low compensation for injecting excess electricity from solar PV back in the grid, and the possibility to receive extra remuneration for providing services (flexibility and exceeding PV generation) to stakeholders as TSO, DSO and BRP (Balancing Responsible Parties) are all incentives for energy community members (i.e.: prosumers and consumers) to fully valorize their flexibility and excess PV generation resources potential for behind-the-meter as well as front-of-the-meter applications.

2.1.3. FleXunity Optimization Solution

The advanced AI-based optimization algorithm developed in “Task 2.3 Community energy assets optimization AI algorithms” of FleXunity project will optimize the operations scheduling of available flexible resources with an aim to maximize the value of consumer flexibility for energy community members (i.e.: prosumers and consumers). More concretely, the optimization algorithm would generate and implement operational decisions for Energy Communities´ distributed energy assets (i.e.: when and how to power the flexible loads, and when and how to charge and discharge the battery/ Electric vehicles) in response to foreseen electricity prices on wholesale market – encouraging energy use at off-peak hours with low prices and discouraging energy use at peak hours with high prices.

After the day ahead scheduling in response to wholesale electricity prices, a heuristic will be performed to inform, in an hourly basis, the flexibility available in the community, more specifically, the controllable loads allocated in each hour that can also participate in demand-side flexibility management programs or in system security services.

3. Flexibility Solutions and FleXunity Business Models

3.1. Flexibility

Since flexibility is defined as a modification of generation injection and/or consumption patterns, therefore for accurate valuation of flexibility, this modification/revised plan must be compared against some reference/baseline (i.e., original schedule or a prediction). Nevertheless, flexibility can be termed as the difference between the baseline (i.e.: original schedule or a prediction) and the revised plan.

The provision of flexibility is called regulation which can occur in two directions: Up and down. Up-regulation calls for increase in generation or decrease in consumption, while down-regulation calls for decrease in generation or increase in consumption.

Figure 3 illustrates in a simplified manner the concept of flexibility. Assume that the green bars represent a baseline consumption and that the orange line represents the revised plan. Then, we have the flexibility for Up-regulation (decrease in consumption) in periods 5, 6, and 7, equal to 4 kW each.

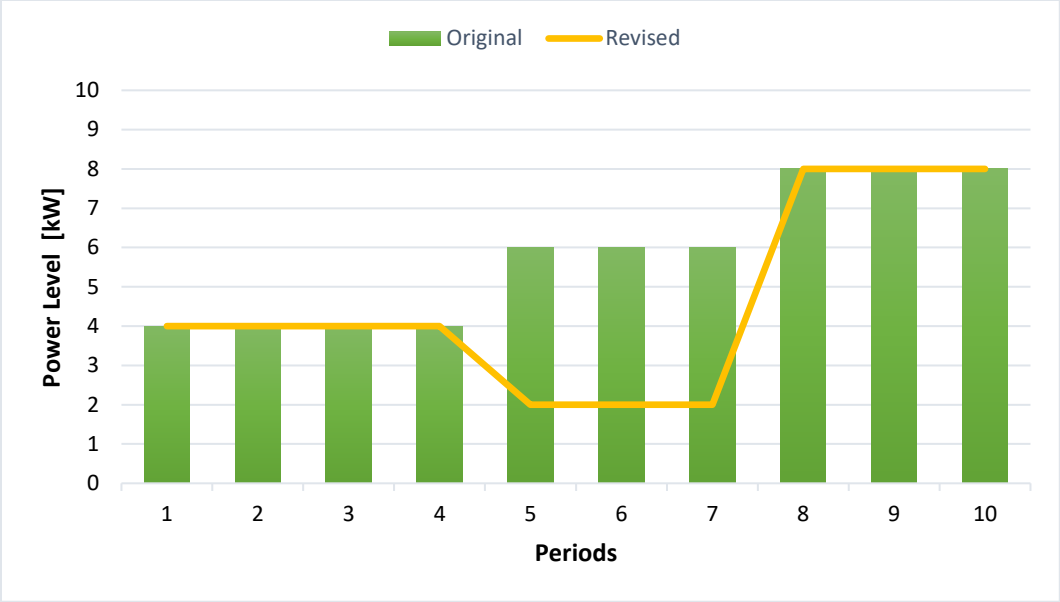

Figure 3 - Original and revised schedule and the provision of flexibility.

3.2. Flexibility Solutions

Energy assets whose generation injection and/or consumption patterns can be modified and controlled, or, at least, programmed, will have the possibility to provide flexibility. Some of the flexible energy assets that are commonly found in building environments are presented in Table 2 and described in more details in the section below.

3.2.1. Flexibility from Loads

Following [14], the energy use appliances can be classified into four different categories according to their ability to respond to external signals (i.e., implicit price signals or explicit activation signals), as follows:

- Controllable Curtailable Appliances (CCA);
- Controllable Uninterruptible Appliances (CUA);

- Controllable Thermostatically Controlled Appliances (C-TCA);

Figure 4 shows the possible baseline consumption of a given energy asset. This baseline consumption would be used to explain the flexibility provision of different categories of flexible assets.

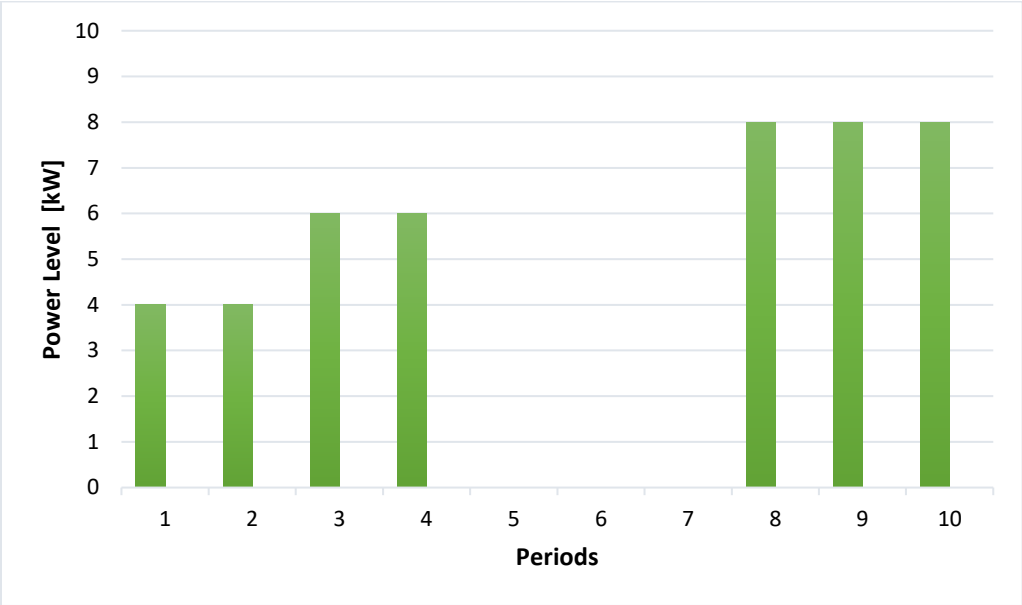

Figure 4 - Baseline consumption.

For instance, we know that Controllable Curtailable Appliances (CCA) can curtail their consumption in response to high electricity prices, or even from request from the system operator. A corresponding example of consumption curtailment can be seen in Figure 5, where the consumption level is curtailed down to 4kW in periods 8 and 9 as compared to baseline consumption in Figure 4.

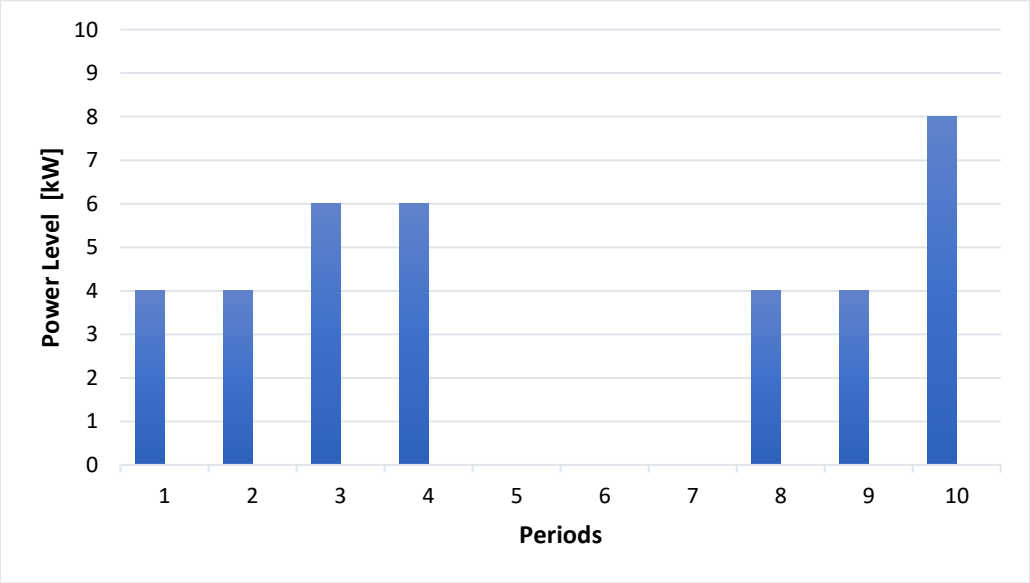

Figure 5 - Flexibility from Controllable Curtailable Appliance (CCA).

Furthermore, Controllable Uninterruptible Appliances (CUA) are considered uninterruptible demands whose use can be shifted to time frames associated with low electricity price. A corresponding example of consumption shifting can be seen in Figure 6, where the consumption level is shifted for three periods as compared to baseline consumption in Figure 4.

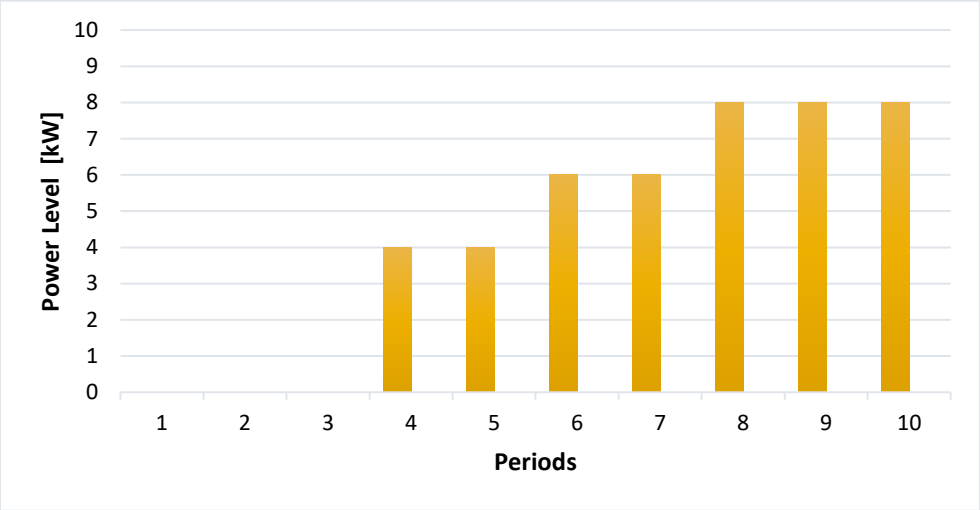

Figure 6 - Flexibility from Controllable Uninterruptible Appliance (CUA).

Additionally, Controllable Thermostatically Controlled Appliances (C-TCA) The C-TCA have thermal storage capability which helps the possibility to shift or anticipate load. Such storage works as an energy buffer, enabling some energy storage during low-price hours to supply the heating needs during the high-price hours. A corresponding example of consumption reduction can be seen in Figure 7, where the consumption level is reduced to zero in periods 8 and 9 as compared to baseline consumption in Figure 4.

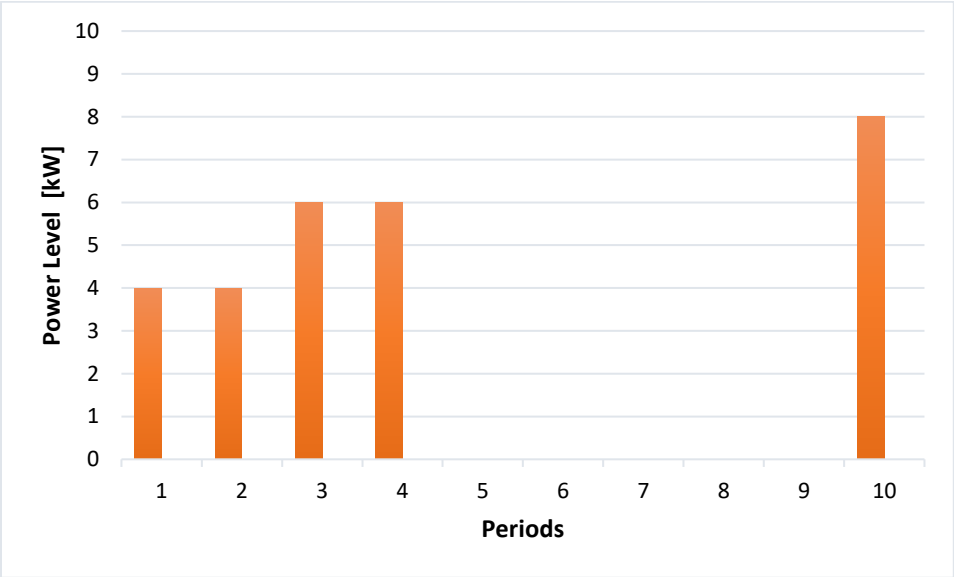

Figure 7 - Flexibility from Controllable Thermostatically Controlled Appliances (C-TCA).

3.2.2. Flexibility from Energy Storage Systems (ESS)

3.2.2.1. Flexibility from Battery Storage Systems (BSS)

Battery Storage Systems (BSS) are generally used to enable the disconnection from the grid, provide local energy balance, or reduce energy costs by charging on low energy prices and selling/using energy on high prices (energy arbitrage). A corresponding example of consumption shifting and shaping can be seen in Figure 8, where the consumption level is shifted and shaped by Battery Storage Systems (BSS) as compared to baseline consumption in Figure 4.

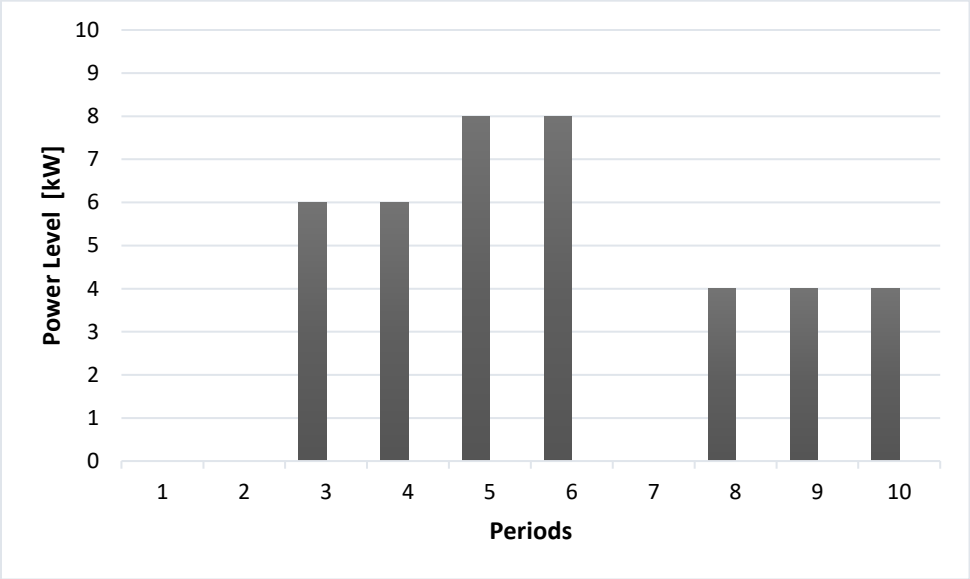

Figure 8 - Flexibility from Battery Storage System (BSS).

3.2.2.2. Flexibility from Electric Vehicles (EVs)

Even though flexibility provision from EVs is comparatively similar to flexibility provision from Battery Storage Systems (BSS), there are additional constraints that must be considered, particularly at a planning stage: Firstly, the constraints related to the availability of electrical vehicles, and secondly, the target state of charge set by the end user must be respected, as means to ensure the availability of certain charge level when the EV is disconnected for use.

3.2.3. Aggregated Flexibility

To provide flexibility for balancing and ancillary services (the main focus of the project), the aggregator/Community Manager must aggregate the flexibility and excess PV generation of energy community members (i.e., prosumers and consumers) to be able to meet the minimum bid volume required to participate in ancillary and flexibility markets. In this context, multi-criteria aggregation models developed in D2.2 –Aggregation models and scheduling methods: Software models and methods of FleXunity project could be used to enable the aggregation of flexibility of small consumers/prosumers and then trade the aggregated available flexibility in existing and emerging ancillary and flexibility markets [3].

Further on the topic of aggregated flexibility, D2.2 – Aggregation models and scheduling methods: Software models and methods implemented has discussed the developments of the FleXunity platform to enable the aggregation of prosumer and consumer flexibility. Additionally, deliverable D2.2 produced detailed assessments of key characteristics of the aggregated flexibility, in terms of requirements of typical products tendered by the balancing and ancillary services markets. These assessments rely on information collected in D2.1 – Legal and technical requirements of balancing markets and D4.1 - TSO balancing markets requirements for EC flexibility services and the result is particularly important for the development.

3.3. FleXunity Business Models

The prosumers and consumers' ability to modify their generation injection and/or consumption patterns could be used for both behind-the-meter and front-of-the-meter applications. For instance, they may choose to self-consume and share their flexibility and excess PV generation within the energy community to reduce their total energy costs Figure 9 or may let an aggregator or Community Manager (CM) trade their services (flexibility and exceeding PV generation) to the stakeholders as TSO, DSO and BRP (Balancing Responsible Parties) (Figure 10).

In this context, the FleXunity project will develop and validate different levels of novel business models covering all relevant stakeholders in the energy value chain, including the Energy community members (i.e.: prosumers and consumers), Retailer/Aggregator Level, and system operators (DSOs and TSOs) as shown in Table 1 **These business models will be discussed in more details in D3.3-New EC Business Models implementation of FleXunity project.**

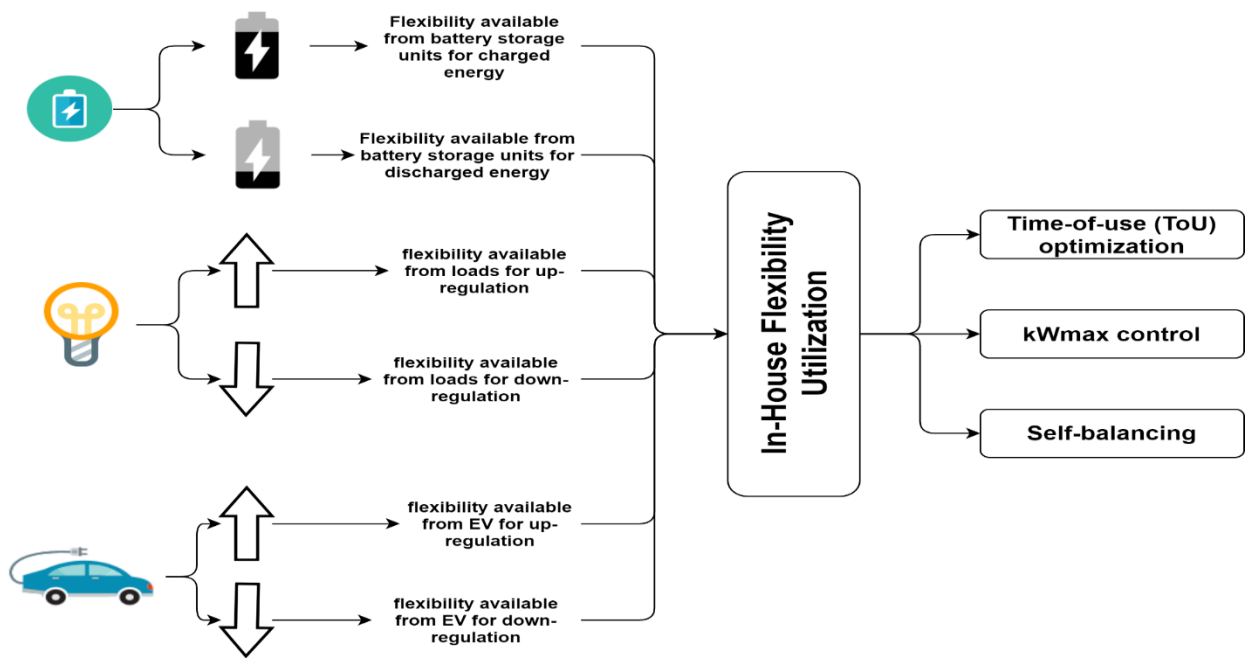

Figure 9 - In-House Flexibility Utilization Opportunities.

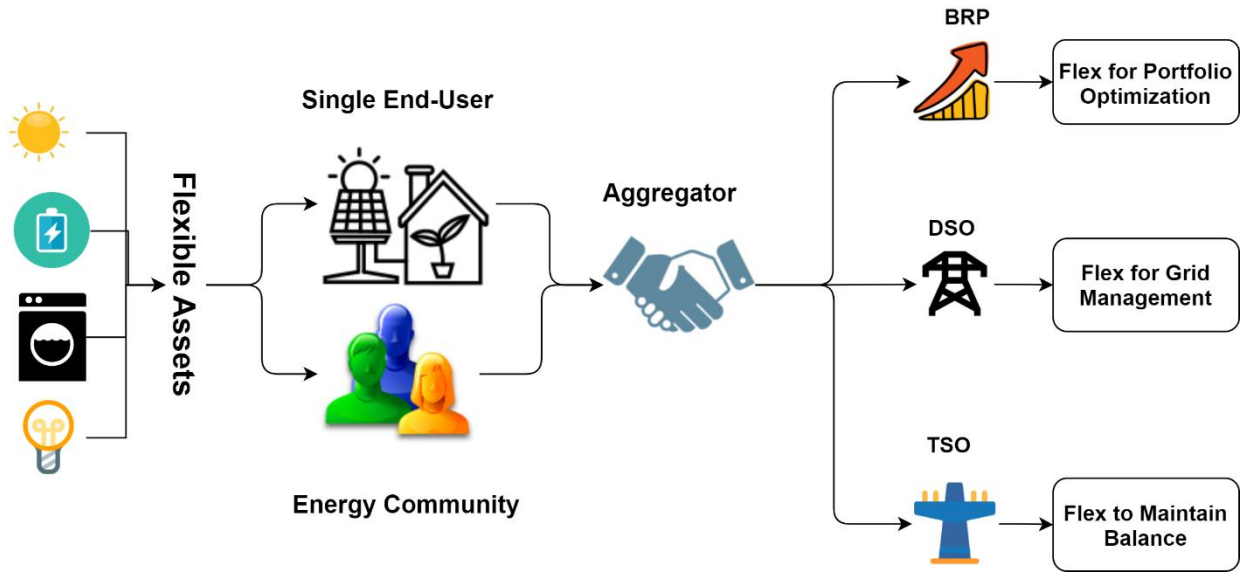

Figure 10 - Flexibility Services to Third parties.

3.3.1. FleXunity End–User Business Model

The FleXunity Business model focused on prosumers and consumers shown in Table 1will validate the self-consumption and sharing of flexibility and exceeding PV generation) of energy community members (i.e.: prosumers and consumers) within the energy community. Prosumers and Consumers can use their flexibility for following applications:

ToU optimization: Flexible resources can be activated whenever possible during low price hours to avoid consumption during high price hours, that could mean shifting flexible resources from morning and evening to night and mid-day. This corresponds to full valorization of local flexibility from flexible resources in response to ToU price.

kWmax control: Flexible resources can be leveraged to contain the overall consumption to kWmax as agreed in the kWmax contract with the grid operator. This corresponds to use of in-house flexibility to avoid paying the higher than the ToU price for consuming every kWh above kWmax.

Self-balancing: Flexible resources can reduce the surplus sales to the grid by exploiting the flexibility of flexible resources locally. This corresponds to the utilization of behind-the-meter flexibility for avoiding the injection of excess electricity from solar PV back in the grid for minimum or no compensation at all.

This Business Model also addresses end-users that want to share their services (flexibility and PV generation) and want to get some compensation for it by selling it to the Community Manager/Aggregator, and the CM/Aggregator will, afterwards, trade those services in balancing and ancillary services.

3.3.2. FleXunity TSO Business Model

FleXunity Business model focused on TSO will validate the TSO´s procurement of flexibility leveraging the FleXunity platform for balancing and ancillary services needs to run the system efficiently.

To maintain the real-time power balance, transmission system operators frequently procure flexible power products (i.e., FCR, aFRR, mFRR, RR etc.) from the market. Historically these flexibility services were provided by traditional large scale polluting power plants [4]. However, in line with the energy transition, these large-scale environmentally unfriendly power plants are expected to be replaced with clean and renewable energy sources such as the wind and solar energy which means that less flexible power products (i.e., FCR, aFRR, mFRR, RR etc.) will be available from conventional power production plants to system operators for balancing purposes in the future [15].

Therefore, it is widely recognized that there is an urgent need to make market for flexible power products (i.e., FCR, aFRR, mFRR, RR etc.) more easily accessible for new market players such as aggregators and energy communities that can aggregate smaller scale assets, renewable generation and/or demand response to continue providing flexibility services to the system in the future [4]. In this context, TenneT, a Dutch (TSO) has conducted a pilot project with many European technology providers to test the delivery of FCR and aFRR with renewables and decentralized assets. This project has concluded that renewables and decentralized assets can deliver FCR and aFRR successfully, which was further confirmed by a third party audit [4].

Similarly, as stated in D4.1 –TSO balancing markets requirements for EC flexibility services, FleXunity platform would also test the delivery of flexible power products listed in Table 3 using Energy Communities´ distributed energy assets (i.e., distributed generation, battery storages, domestic appliances, electric vehicles, heat pumps and HVAC systems etc.).

3.3.3. FleXunity Retailer/Aggregator Business Model

This Business Model presents flexibility as a service provided by the aggregator or Community Manager (CM) to the stakeholders as TSO, DSO and BRP (Balancing Responsible Parties). To provide this service, the aggregator/CM aggregates the flexibility of participants in an energy community as consumers and prosumers.

3.3.3.1. Aggregator/CM's Perspective

This Business Model intends to evaluate the potential value of the actual aggregation and community management business from the Aggregator/CM's Perspective.

3.3.3.2. Retailer's Perspective

BRP procures flexibility for portfolio optimization in wholesale electricity markets (day-ahead, intra-day). For more on BRP services, authors in [19][20][21] have discussed different proposals for addressing the provision of flexibility services to the BRP for portfolio optimization in wholesale electricity markets (day-ahead, intra-day).

This Business Model defines the case in which the retailer will use the local energy market of the energy community for portfolio optimization in the wholesale market.

3.4. Target Flexibility Services for FleXunity Project

Table 4 lists all possible behind-the-meter as well as front-of-the-meter flexibility services that FleXunity Project plans to test and validate in two real world pilots (UK and Iberian).

Table 4 - Flexibility services to be used in each pilot (Y: yes; N: no)

Flexibility Customer	Flexibility Services FleXunity	UK pilot	Iberian pilot
Electricity End-User	ToU optimization	**Y**	**Y**
	kWmax control	**Y**	**Y**
	Self-balancing	**Y**	**Y**
TSO	Frequency Containment Reserve (FCR)	**Y**	**N**
	Automatic/Manual Frequency Restoration Reserve (aFRR/mFRR)	**Y**	**N**
	Replacement Reserve (RR)	**Y**	**N**
DSO	Congestion management	**N**	**N**
	Voltage / Reactive power control	**N**	**N**
BRP	Day–ahead portfolio optimization	**N**	**N**
	Intraday portfolio optimization	**N**	**N**
	Self-balancing portfolio optimization	**N**	**N**

3.5. Markets Status of FleXunity's selected case study countries

Despite Electricity Directive (EU) 2019/944 [10] has set the guidelines for enabling demand side to have a level playing field in all electricity markets in comparison to supply side, market players such as aggregators and energy communities engaged in the demand response and aggregation of demand response are facing many technical, economical, and legal bottlenecks and can´t yet participate fully in all the existing local and upstream electricity markets.

For instance, in Portugal, one of the FleXunity's selected case study countries, the aggregation of small-scale, residential flex-offers including third-party participation for the balancing market or for the provision of ancillary services is not yet possible due to the lack of enabling regulatory frameworks. At present, only two forms of DR services are legislated in Portugal: (i) interruptibility contracts (established by the Ordinance Nr 592/2010); and (ii) regulation reserve services (established by Energy Services Regulatory Authority (ERSE) in Procedure nr. 13 of the Manual of procedures of the global management of the system of the electrical sector), which are nonetheless still subject to many restrictions.

In Portugal, only consumers connected to the Medium Voltage or High Voltage networks can participate in the provision of flexibility services, with a minimum load mobilization capacity cap of 4MW (in the case of interruptibility contracts) or 1 MW (in the case of regulation reserve services). Aggregation is not permitted. Furthermore, detailed assessments of Markets Status of FleXunity's selected case study countries have been provided in D2.1 – Legal and technical requirements of balancing markets.

Summary of Markets Status of all FleXunity's selected case study countries can be seen in

Table 5, Table 6, Table 7 and Table 8).

Table 5 - Markets Status of FleXunity's selected case study countries i.e. Portugal, Spain, and UK.

Stakeholder	Status in the United Kingdom [9]	Status in Spain [22]	Status in Portugal [22]
Balancing and Ancillary Services (TSO)	Possible in GB - TSO accepts aggregated demand response bids for Balancing purposes (third party agreement with the supplier is needed).	Aggregated bids are possible in RR (tertiary control) only.	Aggregated bids are possible in RR (tertiary control) only.
Wholesale Electricity Market (Day ahead, Intraday)	Accessible to Balance Responsible Party.	Accessible to Balance Responsible Party.	Accessible to Balance Responsible Party.

Table 6 - Markets Status of FleXunity's selected case study country (UK) (Y: yes; N: no)

United Kingdom [9] [22]

Type of Markets	**Products**	**Demand Response Access and Participation**	**Aggregated Demand Response Accepted**	**Aggregated Generation**
Wholesale markets	Day Ahead	**N**	**N**	**Y**
	Intraday	**N**	**N**	**Y**
Balancing and ancillary service	Primary Control (FCR)	**Y**	**Y**	**Y**
	Secondary Control (FRR)	**Y**	**Y**	**Y**
	Tertiary Control (RR)	**Y**	**Y**	**Y**
Interruptible Contracts		**Y**	**Y**	**Y**
Capacity Mechanism		**Y**	**Y**	**Y**

Table 7 - Markets Status of FleXunity's selected case study country (Spain) (Y: yes; N: no)

Spain [9][22]

Type of Markets	**Products**	**Demand Response Access and Participation**	**Aggregated Demand Response Accepted**	**Aggregated Generation**
Wholesale markets	Day Ahead	**N**	**N**	**N**
	Intraday	**N**	**N**	**N**
Balancing and ancillary service	Primary Control (FCR)	**N**	**N**	**N**
	Secondary Control (FRR)	**N**	**N**	**N**
	Tertiary Control (RR)	**N**	**N**	**N**
Interruptible Contracts		**Y**	**N**	**N**
Capacity Mechanism		**N**	**N**	**N**

Table 8 - Markets Status of FleXunity's selected case study country (Portugal) (Y: yes; N: no)

Portugal [9][22]

Type of Markets	**Products**	**Demand Response Access and Participation**	**Aggregated Demand Response Accepted**	**Aggregated Generation**
Wholesale markets	Day Ahead	**N**	**N**	**N**
	Intraday	**N**	**N**	**N**
Balancing and ancillary service	Primary Control (FCR)	**N**	**N**	**N**
	Secondary Control (FRR)	**N**	**N**	**N**
	Tertiary Control (RR)	**N**	**N**	**N**
Interruptible Contracts		**Y**	**N**	**N**
Capacity Mechanism		**N**	**N**	**N**

4. Flexibility Models

In an energy community there will be prosumers, who will be able to generate part, or even, the totality of its energy needs (generally considering the balance between energy sold vs. energy bought) and consumers, who will only use energy. Both prosumers and consumers, aiming at lowering their energy costs, need to have electrical appliances that can be controlled, or at least, programmed to work according to a defined setpoint or situation.

Following [14], the energy use appliances/machines can be classified into four different categories as shown in Table 2 according to their ability to modify and control their generation injection and/or consumption patterns in response to external signals (i.e., implicit price signals or explicit activation signals). Besides the controllable loads, there are some uncontrollable ones which consumptions are not or cannot be controlled, such as computers, TVs and cooking devices. It is important to emphasize that despite the natural classification of an appliance/asset into a category, the prosumer/consumer may inform that some "controllable" appliance, in his/her perspective, should be treated as an uncontrolled load.

Generic operational models for different categories of flexible appliances (Table 2) have been developed and discussed in the sections below. These operational models will be used as input data in "FleXunity Optimization Model" whose results will be the operational decisions (operation set-points) (i.e., when and how to power these flexible appliances) with an aim to reduce the overall costs of energy for the energy community members (i.e prosumers and consumers).

4.1. Controllable Curtailable Appliances (CCA)

Curtailable appliances are the demands whose consumption can be curtailed in response to high electricity prices, or even from request from the system operator. CCA can be specific lighting systems, electric heaters without thermostat, water pumps or any other appliance that can be controlled and the consumer/prosumer does not bother if it is turned off for some time. To model such appliances a load prediction/schedule is needed, also when the appliance can be turned off and for how long time.

The scheduling logic for the CCA can also be applied directly in the optimization algorithm where the goal will be to shed such load if the energy price is higher than a predefined price. The CCA can be modeled using:

$$L_t = Max(I_t, a_t) L_{forecasted,t} \qquad \textit{Eq. 1}$$

Where, I_t is a binary indicator (value 0 or 1) if the equipment will be curtailed at time t, a_t is a setpoint indicator (value 0 or 1) that forces the equipment to be turned on according to the consumer/prosumer needs at time t.

Figure 11 shows an example of a possible final load from a controllable curtailable appliance (blue), where the optimization algorithm indicates a load shed between 17 and 19 hours, following the forecasted load (gray), the setpoint where load curtailment is enabled by the consumer (green) and the decision setpoint, where the price allows energy shedding (black).

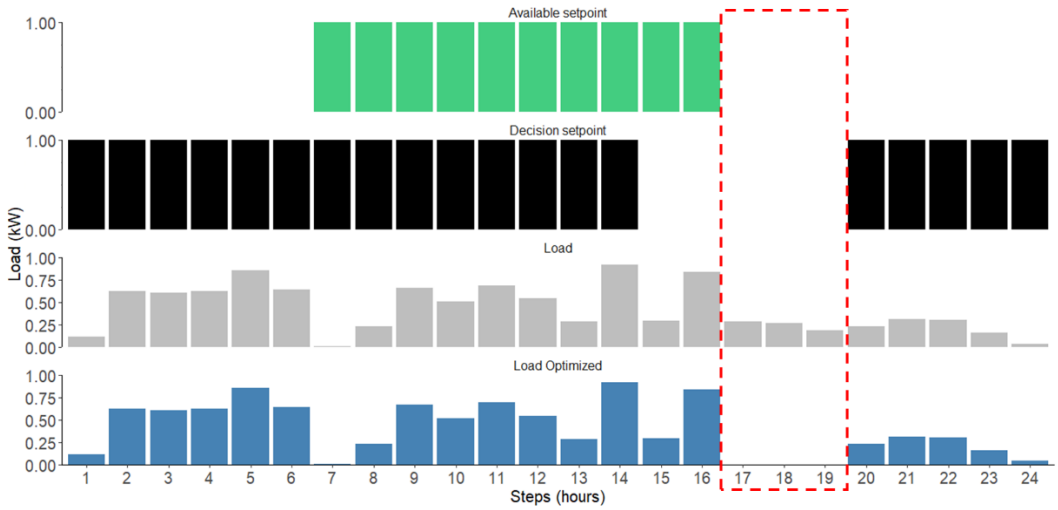

Figure 11 – Example of controllable curtailable appliances optimization

4.2. Controllable Uninterruptible Appliances (CUA)

The CUA are generally wet appliances, i.e., washing machines and dishwashers, that can be considered uninterruptible demands which use can be shifted to time frames associated with low electricity price. They are considered uninterruptible loads because they must run throughout a complete cycle of operations before being turned off or they will not delivery their specific service, e.g., if the washing machine is turned off after the rising stage, the clothes will be clean, but extremely wet.

Uninterruptible loads can be modeled as a fixed quantity of power for a specific consecutive time steps [14]. To model such appliances a few information will be needed, the energy use throughout a cycle, the number of times the appliance will run in a day.

The scheduling logic for the CUA can be applied directly in the optimization algorithm where the goal will be to use a time-frame window with low marginal prices. They can be modeled subject to:

$$\sum_{t=start}^{start+d} I_t a_t = d \qquad \textit{Eq. 2}$$

$$\sum_{t=1}^{24} I_t = d \qquad \textit{Eq. 3}$$

$$1 \leq start \leq 24 - \mathrm{d} \qquad \textit{Eq. 4}$$

Where, $start$ is the start time of the equipment, I_t is an indicator (value 0 or 1) if the equipment is on or off at time t, a_t is a setpoint indicator (value 0 or 1) that allows the equipment to run according to the consumer/prosumer needs at time t.

Figure 12 shows a possible change at the starting time of a washing machine set to a 2-hour program.

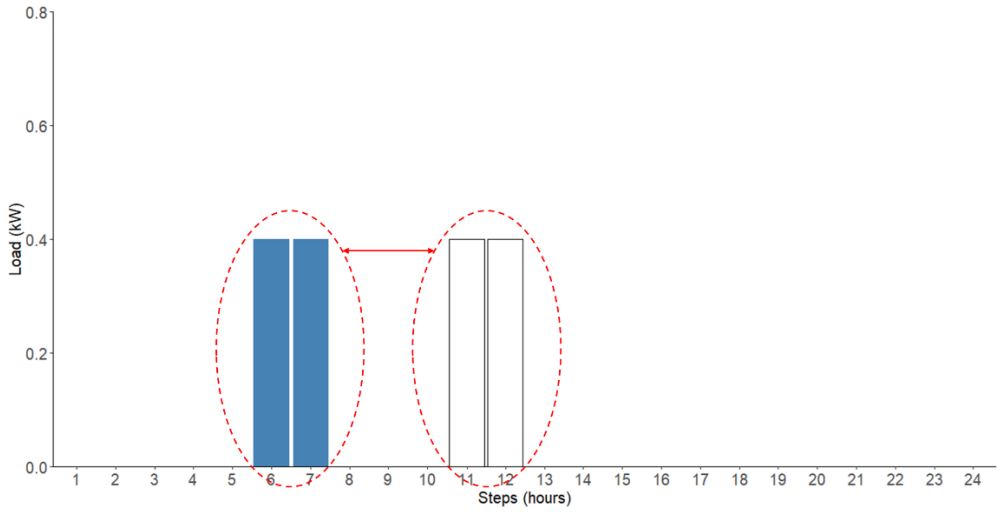

Figure 12 – Example of the control of uninterruptible appliances

4.3. Controllable Thermostatically Controlled Appliances (C-TCA)

The C-TCA have thermal storage capability which helps the possibility to shift or anticipate load. Such storage works as an energy buffer, enabling some energy storage during low-price hours to supply the heating needs during the high-price hours. The flexibility provided by the thermal storage will directly depend on the comfort conditions that will be defined by each prosumer/consumer.

To model the thermal behavior when scheduling C-TCAs [14] suggest to have knowledge about the thermal dynamics of the appliances, which can be modeled following Newton's Laws of Cooling. Such approach tends to give particularly good results when comparing real behavior and the modeled one. However, thermodynamic models tend to be data-intensive, not only on measured data, such as room temperature, outdoor temperature, etc., but also from appliances and houses parameters, such as heat transfer coefficients, coefficient of performance, heat capacity, etc., and tend to be extremely parameter dependent (i.e., if the model parameters are not reliable, the results will not be consistent).

To overcome such issue, it is possible to use (multiple) linear regression models based on measured data from the thermodynamic equations to model the energy use and behavior from C-TCAs [23]. It is also possible to use more complex data-driven tools, such as artificial neural networks (ANNs) or support vector machines (SVMs). Yet, they present a disadvantage in terms of implementation (are more complex to calibrate) and the computational impact would be too high for (near) real-time implementations. Therefore, simple methods, such as linear regression would be preferred, especially when correlation patterns are known or can be easily identified or real-time implementations are desired [24].

In the following subsections, the thermal behavior of following C-TCAs is described.

- Ambient heating/cooling systems.
  - Heaters (heat pumps, air conditioning systems (AC) and electric heaters).
  - Cooling systems (chillers and AC).
- Water heaters.
- Refrigerators

All these C-TCAs have one thing in common; they all have got a temperature controller. Minimum temperature (T_{min}) and maximum temperature (T_{max}) threshold is specified by the end user. To operate the C-TCAs efficiently, temperature setpoint T_t computed by the optimization process must be between $T_{min}$and T_{max} to comply with the comfort conditions defined by each prosumer/consumer. Depending on the appliance, the temperature will be the room temperature (ambient heating and cooling appliances), water temperature (water heaters) or chamber temperature for fridges and freezers. Details about flexibility provision from C-TCAs is presented in Table 9.

Table 9 - Flexibility from C-TCAs.

Flexibility from C-TCAs		
Ambient heating/cooling systems.	$\overline{T}_{max}$ - T_{set}	**Heat storage for preheating the room during the low-price periods.**
	T_{set} - $\underline{T}_{min}$	Heat storage for cooling (reduced consumption during the high energy price periods).
Refrigerators	$\overline{T}_{max}$ - T_{set}	**Heat storage for preheating the chamber during the low-price periods.**
	T_{set} - $\underline{T}_{min}$	Heat storage for cooling (reduced consumption during the high energy price periods).
Water heaters	$\overline{T}_{max}$ - T_{set}	**Heat storage for preheating the water during the low-price periods.**
	T_{set} - $\underline{T}_{min}$	Heat storage for cooling (reduced consumption during the high energy price periods).

From C-TCAs, the energy use and thermal behavior of Ambient heating/cooling systems is modelled only. Other C-TCAs (Water heaters, Refrigerators) energy use and thermal behavior can be modelled using the similar method discussed below.

4.3.1. Ambient heating/cooling systems

Ambient heating and cooling systems are used to provide thermal comfort in a space, which can be a room, a house or even a whole building. The systems can be divided in two:

1. Heaters, which are appliances whose purpose is to increase the temperature in a space to reach some comfort level. Some examples are heat pumps, air conditioning systems (AC) and electric heaters.
2. Cooling systems, generally chillers and AC, provide cooling and/or humidity control for a space.

In general terms, to model any system is important to understand what input parameters are to be studied. Selecting and defining the input parameters is often a difficult task that requires engineering judgement and understanding of the simulation system. Based on heating load equations, Qmodel is a heat load model for cooling based on 8 independent parameters (G, Ti, Tu, Tl, Tamb, Te, Ts and Tn), where G is the Irradiation (W/m2), Ti, Tu, Tl, Tamb, Te, Ts and Tn are, respectively, the temperatures of the inside room, upper room, lower room, outside ambient air, east room, south room and north room (oC). All the parameters can be easily measured, including the Q_a, which is the energy/power spent by the AC to cool the space to find the regression coefficients to effectively use the model to operate the AC. If any of the rooms surrounding the AC room does not exist, it can be removed from the equation.

Therefore, the linear model to describe the thermal behavior of the AC can be used as follows:

$$Q_a = \beta_0 + \beta_1 G + \beta_2 T_i + \beta_3 T_u + \beta_4 T_l + \beta_5 T_{amb} + \beta_6 T_e + \beta_7 T_s + \beta_8 T_n \qquad \textit{Eq. 5}$$

To find the internal temperature, the original equation is rearranged and a lag (Ti-1) for the ambient temperature is added to improve the model and give the heat inertia information following. Ti-1 is the temperature inside room in the previously hour.

$$T_i = \beta_0 + \beta_1 G + \beta_2 Q_a + \beta_3 T_u + \beta_4 T_l + \beta_5 T_{amb} + \beta_6 T_e + \beta_7 T_s + \beta_8 T_n + \beta_9 T_{i-1} \qquad \textit{Eq. 6}$$

To estimate the coefficients for each predictor variable a sample data must be provided. With data in hands, a least-squares approach can be used to estimate the parameters of a set of explanatory variables by minimizing the sum of the squares of the differences between the observed values and those predicted by the linear function of the dependent variable (T_i).
After finding the coefficients, the model should look like:

$$T_i = \beta_0 + \beta_1 G + \beta_2 Q_a AC_{on} + \beta_3 T_u + \beta_4 T_l + \beta_5 T_{amb} + \beta_6 T_e + \beta_7 T_s + \beta_8 T_n + \beta_9 T_{i-1} \qquad \textit{Eq. 7}$$

Subject to:

$$\underline{T_i} \leq T_i \leq \overline{T_i} \qquad \textit{Eq. 8}$$

$$0 \leq Q_a \leq Q_{nominal} \qquad \textit{Eq. 9}$$

Where $\underline{T_i}, \overline{T_i}$ are the lowest and highest temperature accepted, $Q_{nominal}$ is the nominal machine power and AC_{on} is a decision binary variable to turn the AC on (1) or turn it off (0).

Since cooling or heating is a matter of putting energy inside the room or “removing” energy from it, the cooling model can also be used for heating.

It is important to fit the model with measured data and verify its consistency before using it.

4.4. Energy Storage Systems (ESS)

Technologies based on energy storage systems (ESS) are generally used to enable the disconnection from the grid and provide local energy balance or to reduce costs by charging on low energy prices and selling/using energy on high prices. Here, ESS are not limited to charge from local energy sources, such as rooftop solar photovoltaics (PVs), therefore being able to charge also from the grid and perform energy arbitrage. Electric Vehicles (EVs) are considered a particular case of ESS.

An ESS can be modeled following:

$$C_{ESS_t} = C_{ESS_{t-1}} + (1 + L_D I(P_t < 0) - L_C I(P_t > 0))\, P_t A \qquad \textit{Eq. 10}$$

Subject to:

$$\frac{-P_D}{1+L_D} \leq P_t \leq \frac{P_C}{1-L_C} \qquad \textit{Eq. 11}$$

$$C_{ESS_{Min}} \leq C_{ESS_t} \leq C_{ESS_{Max}} \qquad \textit{Eq. 12}$$

$$C_{ESS_{tEnd}} \geq C_{ESS_{Target}} \qquad \textit{Eq. 13}$$

Where C_{ESS_t} is the charge of the battery at time t, $C_{ESS_{Min}}$ and $C_{ESS_{Max}}$ is the minimum and maximum energy stored, L_C and L_D are the losses for charging and discharging ($L = 1 - \eta$), η is the efficiency, $I(P_t)$ is an indicator 1 when true and 0 when false, P_t is the power to charge or discharge at time t, P_D and P_C are the maximum power charge and discharge, A is the availability indicator, being 1 when connected and 0 when disconnected (e.g., EVs may be off the community when serving as mobility device), $C_{ESS_{tEnd}}, C_{ESS_{Target}}$ are the charge at the end of the window connected, and the target charge at the end of the window (e.g., one may set a minimum charge value so that the car can be used for mobility when disconnected from the grid).

The model can be applied in the optimization algorithm to find the most fitted P_t according to the energy price.

4.5. Uncontrollable Loads (UL)

Uncontrollable loads are energy uses that are not or cannot be controlled, such as computers, TVs and cooking devices. The electricity consumption of such appliances can be modeled with an hourly load profile that must be supplied by the grid or by the community's manager. Figure 13 shows an example of an uncontrollable load in a 24-hour time span.

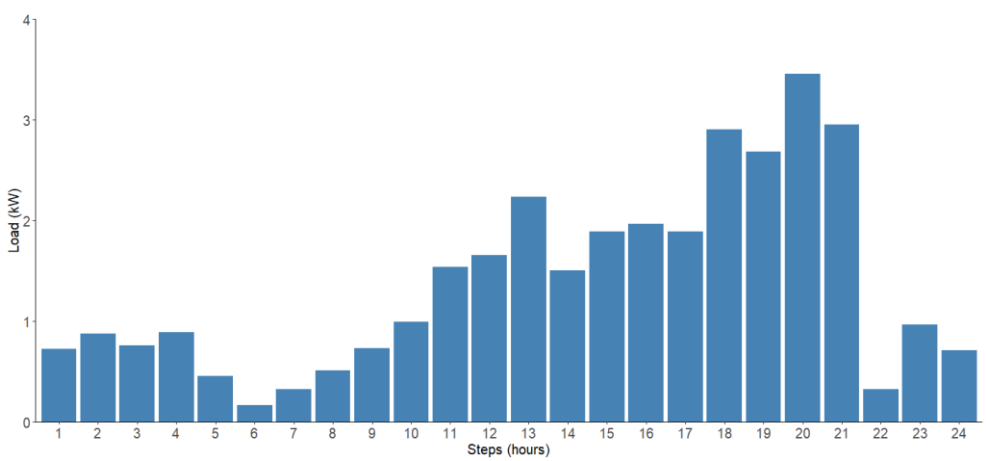

Figure 13 – Example of uncontrollable load.

4.6. Energy Generation

On the small-scale energy supply side, one can find the most common generators as the small wind generators and rooftop solar photovoltaics. Those are installed at the prosumer dependencies and aim to generate electricity to reduce the energy bill. Since there is no control on such devices, i.e., they rely on the availability from the respective renewable energy resource, the supply assets are modeled simply applying a forecast generation curve to the optimization algorithm. Figure 14 shows an example of a PV generation curve that can be given to the optimization algorithm.

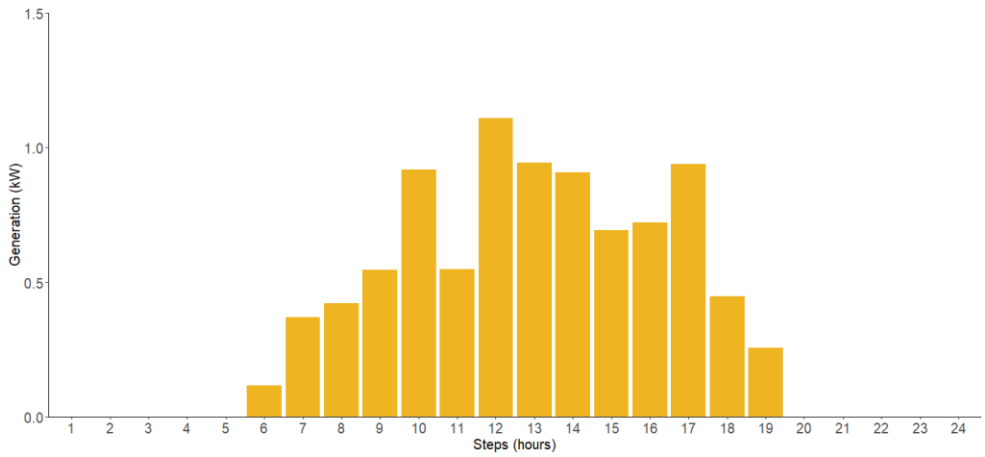

Figure 14 – Example of a PV generation.

5. FleXunity Community Energy Assets Optimization

5.1. FleXunity Optimization Model

A complete mathematical model for FleXunity optimization problem described in "FleXunity Problem description" is presented in "Mathematical Formulations" which comprises of the operational models of (C-CTA, CCA, CUA and ESS) each type of appliance that can be controlled, other type of data inputs (such as uncontrollable loads and local generation), the global and local constraints applied to the optimization model, the decision variables, and the objective function to the optimization problem.

Furthermore, the Figure 15 presents a simplified flowchart of the data stream for each possible modeled load and generation for each individual consumer/prosumer. There are six data sources for both load and generation assets and one for pricing/tariff which are described in more details in "Input Data for FleXunity Optimization Model".

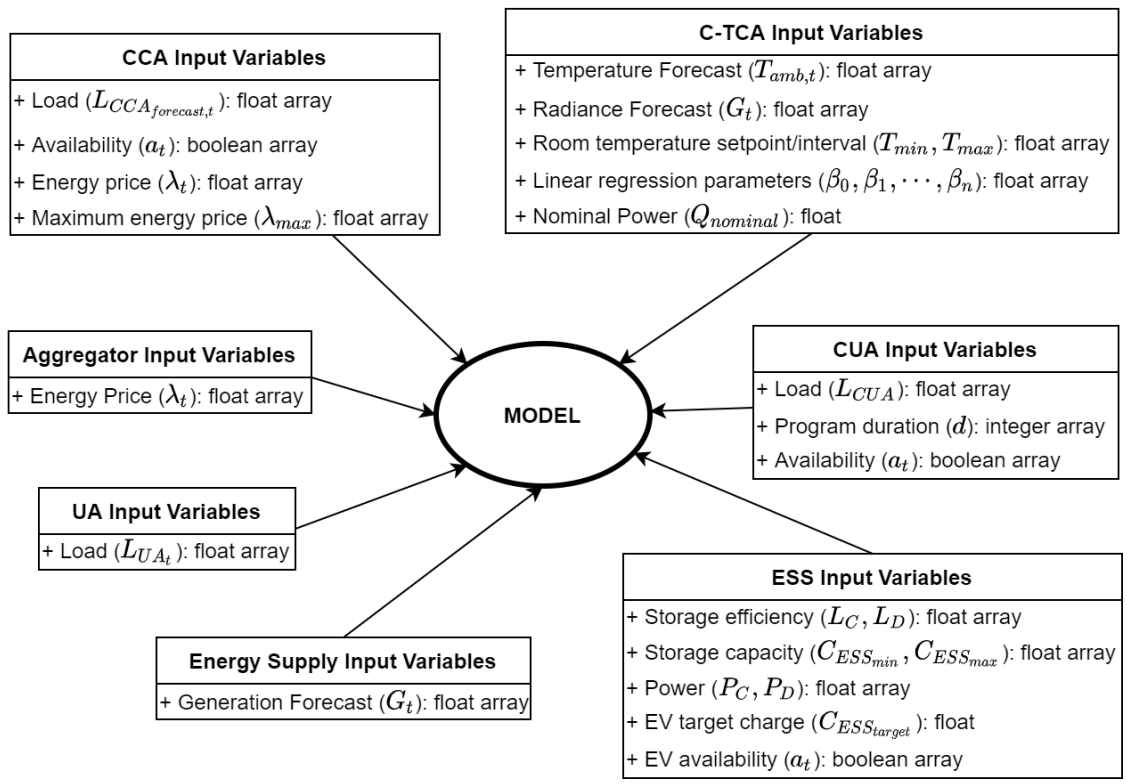

Figure 15 – Data input simplified flowchart.

The output of such an optimization model as shown in Figure 16 would be a day ahead scheduling of all appliances belonging to the consumers/prosumers, i.e., the energy needed/generated at each hour of the day. Having the scheduling optimization finished and knowing the day ahead loads at each hour, it is possible to identify which loads are the controllable ones. The controllable loads can, therefore, be offered to participate in demand-side flexibility management programs or in system security services.

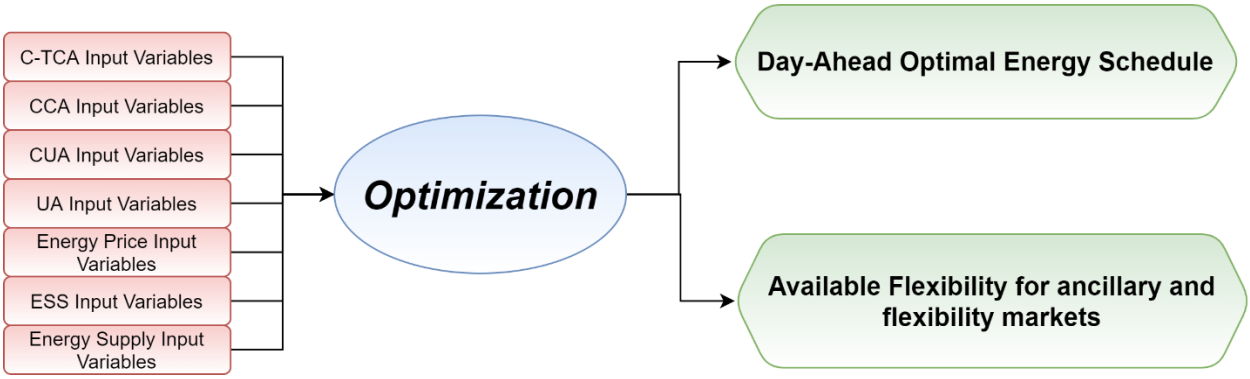

Figure 16 Data Input-Output simplified flowchart process.

5.1.1. Solution Approaches to Optimization Problem

There are many of techniques available to solve the type of optimization problems formulated in "FleXunity Optimization Model". Such problems try to schedule flexible loads according to the local renewables' energy generation and a dynamic pricing for the energy from/to the grid, being solved in published literature mainly via the solution techniques enlisted in Table 10. Examples of dynamic pricing can be the time-of-use (TOU) pricing, where intra-day variations in price of electricity are set for a specific period in advance [25] or when a retailer determines the hourly electricity price for the consumers [14]. Both examples follow the same idea, to inform beforehand the prices so that the consumers may organize their consumption according to their wiliness (and possibility) to pay.

Table 10 - Solution Techniques for Optimization Problems.

Solution Approaches	
Mathematical programming	Linear Programming (LP)
	Mixed Integer Linear Programming (MILP)
	Nonlinear programming (NLP)
Heuristic approaches	List Processing
	Markov Decision Process
Meta-heuristic approaches	Genetic Algorithm
	Particle Swarm Optimization
	Ant Colony Optimization
	Grey Wolf Optimization
	Knapsack

Furthermore, Comparison of literature on similar optimization problems and relevant solution approaches is presented in Table 11.

Table 11 - Comparison of literature on Optimization Problems and Solution Approaches.

Problem	Type	Objective	Solution Technique
Appliance Scheduling [26]	Nonlinear programming (NLP)	Cost Minimization	Particle swarm optimization
Consumption Scheduling [27]	Mixed-Integer Linear Programming (MILP)	Cost Minimization	Centralized Optimization
Consumption Scheduling [28]	Linear programming (LP)	Cost minimization and PAR reductions.	Game Theory
Shiftable devices scheduling [29]	Mixed-Integer Linear Programming (MILP)	Max-self consumption	Heuristic algorithm using a PV-indexed dynamic tariff
Consumption Scheduling [30]	Multi-Objective Optimization	Min cost, consumption, PAR reductions.	Combinatorial Optimization for Heuristic for Distributed Agents

The day ahead energy scheduling problem to be tackled is a time horizon problem, that grows in complexity following three dimensions, the number of periods (i.e., the number of hours in a day), the number of appliances in each prosumer/consumer and the number of consumers/prosumers.

This problem is solved in literature in several manners, such as using mathematical programming (e.g., Linear Programming (LP) and Mixed Integer Linear Programming (MILP)), heuristic approaches (e.g., List Processing and Markov Decision Process) and meta-heuristic approaches (e.g., Genetic Algorithm and Particle Swarm Optimization). As size and complexity of the optimization problem increases with the additions of more variables and restrictions, solution of such optimization model using classical mathematical programming techniques become increasingly complex and the use of meta-heuristic approaches (e.g., Genetic Algorithm and Particle Swarm Optimization) become inevitable [29]. Classical mathematical programming methods guarantee optimal solution, while meta-heuristic approaches (e.g., Genetic Algorithm and Particle Swarm Optimization) don´t guarantee the globally optimal solution [31].

In smart grid era, signals for energy prices, the local energy generation, and the energy demand change frequently requiring to re-run the optimization process with latest information. Thus, development of FleXunity optimization model has considered this trade off the optimal solution for reduced computation time.

5.2. Input Data for FleXunity Optimization Model

This section organizes the input data needed for the day-ahead scheduling of controllable load and generation. Most of the input data was based on the “Flexibility Models” section, and it aims to be a compromise between accuracy of the desired model’s outputs and availability, accessibility, and censoring cost.

Following, the time-of-use pricing or a simulation/prediction of the day ahead energy market prices was assumed as one of the main input data, considering that the optimization algorithm will schedule the controllable load and generation according to the variations of such predefined prices/tariffs.

The data input modules are described in more detail in the following subsections.

5.2.1. Energy Supply Input Data

The energy supply input variables that enter the optimization model must be provided by a forecast process/service which may be provided by external sources or computed with use of a prediction module. The input data for the forecast process are not covered in this section, nevertheless, some insights on data needed for the forecast process are raised.

5.2.1.1. Possible data needed for the forecast process

If the forecast process is technology driven, it will need a few electrical/technical data about the generator (e.g., rooftop PV), such as maximum power output, voltage and current operational curve, efficiency curve over temperature, etc. Such data is generally needed to convert weather forecasts/measurements, such as irradiation and ambient temperature, to energy generation following engineering models. However, the translation between weather data and energy can be also done using data driven models, i.e., using weather dada and measured energy generation to build such transference curve/model.

Generally, the energy forecast models are based on external data provided by weather forecast models. The weather forecast models bring the possible future weather conditions for a specific time frame and for a specific location. For rooftop PV systems, the weather data needed are basically ambient temperature, which affects the efficiency of the modules, and the actual irradiance that is the energy from the sun that will be converted into electricity.

5.2.1.2. Energy supply data

Since there will not be any control on the generation side, as most microgeneration systems, such as rooftop PV and mini wind turbines, have almost no control and rely on renewable resource condition, the only generation data needed for the optimization algorithm will be a float array with a size of 24 elements (supposing it will be a 24-hour schedule). One value for each expected generation in each hour of the next day. Again, since the algorithm will not control such generation, the aggregation process of multiple generation units can occur previously to the model, having only one array with the total energy generation for each hour as data input, or several arrays of data can be provided to the algorithm for each generation unit for internal aggregation. The following table presents the input data.

Table 12 – Energy generation data.

Data	Type	Size	Unit	Comments
Energy supply data (G_t)	float array	24	(k)Wh	One array for each system or a single array for an aggregated generation

5.2.2. Uncontrollable Loads (UL) Input Data

The required input data for the representation of the UL in the optimization algorithm were assessed from its description presented in the "Flexibility Models" section. The UL data is based on the energy consumption of all the non-controllable appliances for each hour of the day. Such data can be retrieved from a forecast model/module, from estimations given by each prosumer/consumer based on what they expect from the use of their appliances during the next day or from an energy profile from historical data. The first two data sources tend to be more reliable than an energy profile, which is generally fixed for a period or for a group of days.

User/forecast input data:

- Load (L_{UL_t}): Sum of all the energy consumption from every appliance that cannot be controllable in (k)Wh for each hour. This is a float array with size 24 (assuming 24-hour period) for each consumer.

The following table presents the uncontrollable load input data.

Table 13 – Uncontrollable Load data.

Data	Type	Size	Unit	Comments
Load (L_{UL_t})	float array	24	(k)Wh	One array for each consumer

5.2.3. Energy Storage System (ESS) Input Data

The required input data for the representation of the ESS in the optimization algorithm were assessed from the model description presented in the ESS subsection from the "Flexibility Models" section. For each ESS there will be two groups of input data, the system data and the user input data or setpoint data. The system data are a group of information concerning technical aspects of each ESS, such as power output. The user input data are setpoints defined by the ESS owner expressing mandatory availability of such systems, such as minimum charge for an electric vehicle (EV) at the defined disconnection time. The input date is described in more detail bellow.

System data:

- Power discharge (P_d): Maximum power output from the ESS system in (k)W. This is a single float variable for each system.
- Power charge (P_c): Maximum power input or maximum load of the ESS system in (k)W. This is a single float variable for each system.
- Energy capacity (C_{ESS}): The maximum energy that the ESS can store in (k)Wh. This is a single float variable for each system.
- Power capacity (P_{ESS}): The maximum power that the ESS can supply in (k)W. This is a single float variable for each system.
- Storage/charge losses (L_c): The losses from the storage process, dimensionless. This is a single float variable for each system.

- Discharge losses (L_d): The losses from the discharge/energy generation process, dimensionless. This is a single float variable for each system.
- Storage state at start time ($C_{ESS_{t_0}}$): The energy stored in the ESS at the beginning of the scheduling process in (k)Wh. This is a single float variable for each system.
- Minimum storage capacity ($\mathrm{C_{ESS_{min}}}$) and maximum storage capacity ($\mathrm{C_{ESS_{max}}}$).
- Battery degradation rate.

User input data:

- EV/ESS availability (a): Binary variable that can assume two states, 1 when the electric vehicle is connected to the grid and is working as an ESS at a specific time, and 0 when the EV is disconnected and cannot be operated. This is a Boolean array with size 24 (assuming 24-hour period) for each system. From this array it is possible to identify the last hour that the system is connected ($C_{ESS_{t_{End}}}$), which is also an important variable to the optimization algorithm.
- EV/ESS target charge ($C_{ESS_{t_{target}}}$): The minimum charge allowed at the battery at the end of the operation time frame. This input data is important to give the model a target to build its schedule process to respect the final use of the EV, that is to be charged for mobility purposes. This is a single float variable for each system.

The following table resumes the ESS input data.

Table 14 – ESS input data

Data	Type	Size	Unit	Comments
Power discharge ($\mathrm{P_d}$)	float	1	(k)W	One value for each system
Power charge ($\mathrm{P_c}$)	float	1	(k)W	One value for each system
Energy capacity ($\mathrm{C_{ESS}}$)	float	1	(k)Wh	One value for each system
Storage/charge losses ($\mathrm{L_c}$)	float	1	-	One value for each system
Discharge losses ($\mathrm{L_d}$):	float	1	-	One value for each system
Storage state at start time ($\mathrm{C_{ESS_{t_0}}}$)	float	1	(k)Wh	One value for each system
EV/ESS availability (a)	Boolean array	24	-	One array for each system
EV/ESS target charge ($\mathrm{C_{ESS_{t_{target}}}}$)	float	1	(k)Wh	One value for each system

5.2.4. Controllable Uninterruptible Appliances (CUA) Input Data

As the uncontrollable loads, the CUA required input data for the optimization algorithm were assessed from the model description presented in the CUA subsection from the "Flexibility Models" section. For CUA, the user must set the availability of the appliances for each hour of the 24 hours of the next day and the expected program from each appliance that must work on the next day. It is also required the program duration and the estimated energy consumption by the appliance. For simplification purposes, especially simplification on data requirement, it is assumed that the energy consumption is the same in each step (hour).

System data:

- Load (L_{CUA}): Appliance's estimated energy consumption, in (k)Wh, for a certain program. For the proposed model, this data is considered constant through all the program duration. This is a float array with 24 equal values for each system.
- Program duration (d): Duration (hours) of the predefined appliance program. For instance, the time a washing machine needs to complete its washing cycle. This is an integer variable for each system.

User input data:

- Availability (a): Binary variable that can assume two states, 1 when the appliance is available to be scheduled, and 0 when the user defined that the appliance cannot be function during such period. This is a Boolean array with size 24 (assuming 24-hour period) for each system.

The following table presents the CUA input data.

Table 15 – Controllable Uninterruptible Appliances input data.

Data	***Type***	***Size***	***Unit***	***Comments***
Load (L_{CUA_t})	float array	24	(k)Wh	One array for each consumer
Program Duration (d)	integer	1	h	One value for each consumer
Availability (a_t)	Boolean array	24	-	One array for each consumer

5.2.5. Controllable Curtailable Appliances (CCA) Input Data

The CCA follows the description found at the "Flexibility Models" section, does not only require system and user input data, but also the energy price from the aggregator, system operator or any other source used. Besides the availability of each appliance to be curtailed by the optimization process, the prosumer/consumer must also provide the maximum energy price they are willing to pay to have such load turned on. This trigger was introduced because if the consumer/prosumer allows an appliance to be shut down, following the definition of minimum cost, the algorithm will always decide to curtail such load,

unless the tariff/price is negative. Therefore, such setpoint gives some flexibility to the curtail process following some economic preference from the prosumer/consumer.

System data:

- Load ($L_{CCA_{forecast,t}}$): The appliance's estimated/forecasted energy consumption, in (k)Wh, for each hour t. This is a float array with size 24 (assuming 24-hour period).
- Energy price (λ_t): The energy price forecast (€/(k)Wh) to assess curtailable status of the load. This is a float array with size 24 (assuming 24-hour period).

User input data:

- Availability (a): Binary variable that can assume two states, 0 when the appliance is available to be curtailed by the aggregator, and 1 when the user imposed the appliance operation. This is a Boolean array with size 24 (assuming 24-hour period) for each system.
- Maximum energy price ($\lambda_{\max}$): The energy price (€/(k)Wh) threshold from which the user allows the load to be curtailable, i.e., if the $\lambda_t \leq \lambda_{\max}$ even when $a_t = 0$ the model will not allow the load to be cut. This is a single float variable.

The following table presents the controllable curtailable appliances input data.

Table 16 – Controllable Uninterruptible Appliances input data.

Data	Type	Size	Unit	Comments
Load ($L_{CCA_{forecast,t}}$)	float array	24	(k)Wh	One array for each consumer
Energy price (λ_t)	float array	24	€/(k)Wh	One array for each consumer
Maximum energy price (λ_{max})	float	1	€/(k)Wh	One value for each consumer
Availability (a_t)	Boolean array	24	-	One array for each consumer

5.2.6. Controllable Thermostatically Controlled Appliances (C-TCA) Input Data

The required input data for the representation of the C-TCA in the optimization algorithm were assessed from the model description presented in the "Flexibility Models" section. In addition to the system and user input data, the C-TCA also require weather (forecast) data to provide the temperature and radiance values required by the model.

System data:

- Linear regression parameters ($\beta_0, \beta_1, \cdots, \beta_n$): The linear equation coefficients provided by a pre-trained linear regression model. This is a float array with size of the number of coefficients required for each type of C-CTA (n_{parms}).

- Nominal Power ($Q_{nominal}$): Maximum power output from the C-CTA system in (k)W. This is a single float variable for each system.
- Surrounding temperatures: The expected/forecasted surrounding temperatures. This input data can be applied to ambient heating or cooling to improve the quality of the model by the cost of more data measurements/forecasts. Possible data entries can be temperatures for the upper room (Tu), lower room (Tl), east room (Te), west room (Tw), south room (Ts) and north room (Tn). All data must be in oC. They are a float array with size 24 for each room available.
- Water use (m): The expected/forecasted mass of water retrieved from the storage of the water heaters at each hour of the day.

Weather forecast data:

- Temperature ($T_{amb,t}$): Expected temperature for each hour for the next day in oC for the location of the consumer/prosumer.
- Irradiance (G_t): Forecasted solar irradiance for each hour for the next day (W/m2). This data is also specific for each location.

User input data:

- Internal room/storage minimum temperature interval (T_{min}, T_{max}): Allowed temperature interval set by the user. Each temperature must be in oC. Depending on the appliance, the temperature will be the room temperature (ambient heating and cooling appliances), water temperature (water heaters) or chamber temperature for fridges and freezers. This is a float array with size 2 (lower and upper bounds) for each system.

The following table describes the C-CTA input data.

Table 17 – Controllable Thermostatically Controlled Appliances input data.

Data	Type	Size	Unit	Comments
Temperature forecast ($T_{amb,t}$)	float array	24	°C	One array for each system
Irradiance forecast (G_t)	float array	24	W/m^2	One array for each system
Room/storage temperature (T_{min}, T_{max})	float array	2	°C	One array for each system
Linear regression parameters ($\beta_0, \beta_1, \cdots, \beta_n$)	float array	n_{parms}	-	One array for each system
Nominal Power ($Q_{nominal}$)	float	1	(k)W	One value for each system
Surrounding temperature - upper room (T_u)	float array	24	°C	One array for each system – non mandatory

Surrounding temperature - lower room (T_l)	float array	24	°C	One array for each system – non mandatory
Surrounding temperature - east room (T_e)	float array	24	°C	One array for each system – non mandatory
Surrounding temperature - west room (T_w)	float array	24	°C	One array for each system – non mandatory
Surrounding temperature - south room (T_s)	float array	24	°C	One array for each system – non mandatory
Surrounding temperature - north room (T_n)	float array	24	°C	One array for each system – non mandatory
Water use (m)	float array	24	kg	One array for each system

5.2.7. Community Manager input data

The Community Manager is defined here as the central system and responsible to collect data from the consumers/prosumers, the forecast modules/services and retrieve the predicted or negotiated tariffs for the next day. The Community Manager is also responsible to execute the day ahead schedule optimization to obtain the energy needed or available to be sold for the next day. The Community Manager also gets the available flexibility from the optimization process and can negotiate such energy use on the respective markets (e.g., ancillary services market).

System data:

- Energy price (λ_t): Energy price forecast (€/(k)Wh) provided by the aggregator or system operator. This is a float array with size 24 (assuming 24-hour period).

Table 18 – Community Manager input data.

Data	Type	Size	Unit	Comments
Energy price (λ_t)	float array	24	€/(k)Wh	One array for each consumer

5.2.8. Forewarning

It must be stressed that both renewable generation and weather data are directly affected by the uncertainty inherited from the weather forecast modules/services. Such forecast models and services can be more or less accurate but will never be 100% precise. This fact will propagate some uncertainty throughout the optimization process.

It should be also emphasized that the load input data also present uncertainties regarding measurement and, specially, associated with each consumer behavior. Such uncertainty may introduce a gap between the expected load, that will be used in the optimization process, and the real load accounted.

6. Mathematical Formulations

In this study is assumed that each member of the energy community has a smart control system which receives setpoints from a central system responsible for the energy schedule and optimization. The aim of the energy community schedule is to minimize the cost of energy consumption satisfying the comfort constraints of its members. Comfort setpoints of each appliance are determined and set by each appliance owner.

The mathematical model, for clarity purposes, was divided into four partial modules (C-CTA, CCA, CUA and ESS), regarding each type of appliance that can be controlled. The uncontrolled appliances, such as uncontrollable loads and local generation are input data that pass through the model to the output schedule. The data inputs, the constraints applied to the model and the identified decision variables, which enters the objective function, are also presented. A complete model is proposed referencing the partial modules, which describes the global restrictions and the objective function to the optimization problem.

The input data are the mandatory parameters required by the module constraints, which are the restrictions that may be technical (maximum output power, load-generation balance, etc.) or user specifications (electrical vehicle availability). Finally, the decision variables are the variables which the model is "allowed" to change to reduce the total energy cost, for example, which time the electrical vehicle will be charged.

After the scheduling process, it is performed a heuristic to inform, in an hourly basis, the flexibility available in the community, more specifically, the controllable loads allocated in each hour that can also be shed to participate in demand-side flexibility management programs.

6.1. Controllable Thermostatically Controlled Appliances (C-TCA) module

For the thermic loads that can be thermostatically controlled, the model computes the temperature setpoint T_t that must be between $T_{min}$and T_{max}, which each thermic appliance should operate at the time t, while the restrictions imposed by 4.3.1 being satisfied. For that, the input variables $T_{amb,t}$, G_t, T_{min}, T_{max}, $\beta_{0...n}$ and $Q_{nominal}$ must be provided. The output variable is Q_t, which represents the energy required to maintain the temperature T_t.

In this case, the decision variable and the module output can be simplified to a single decision (Q_t) variable expressing the controlled energy of the system, although, this is not always the case, especially when the control system can only turn the load on and off.

It should also be stressed that the temperature for the hour t depends on the temperature on the previously hour (t-1), therefore the module is not memoryless, and it represents the thermal inertia of the system.

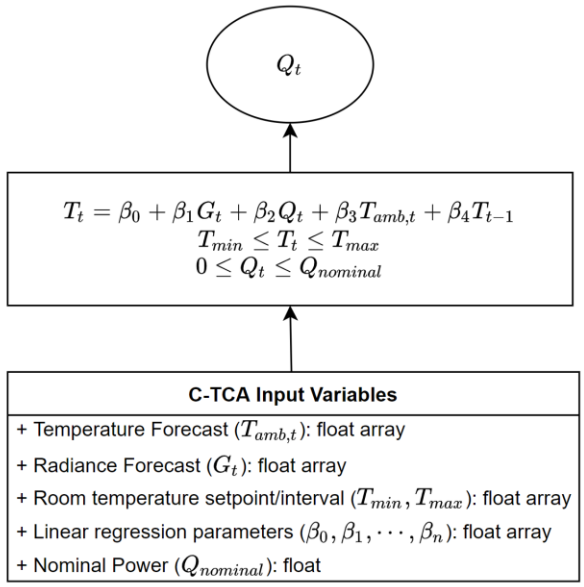

Figure 17 – Controllable Thermostatically Controlled Appliances module workflow.

6.1.1. Module Requirements

Each thermic load introduces three constraints to the model, the temperature equation in respect to Q_t, the temperature (T_t), where the user specifies the upper and lower bounds (T_{min}, T_{max}) and the maximum load ($Q_{nominal}$). Also, five groups of input variables are necessary for the calculation.

6.2. Controllable Curtailable Appliances module

The controllable curtailable appliances (CCA) are quite simple to model, they must be turned on when the user defines, or they can be turned off for the other hours, if the energy price is higher than a predefined value.

For each CCA, the input variables a_t, $L_{CCA_{forecast,t}}$ and λ_{max} must be provided to find the decision variable I_t. I_t assumes 1 when $L_{CCA_{forecast,t}}$ is in use, and 0 when $L_{CCA_{forecast,t}}$ is not, following:

$$I_t \begin{cases} Max(0, a_t), \lambda_t > \lambda_{max} \\ Max(1, a_t), \lambda_t \leq \lambda_{max} \end{cases} \quad \text{Eq. 14}$$

$$a_t \in \{0,1\} \quad \text{Eq. 15}$$

The equation above means that if the user does not allow the load to be shed, then L_{CCA_t} is always turned on (when $a_t = 1$).

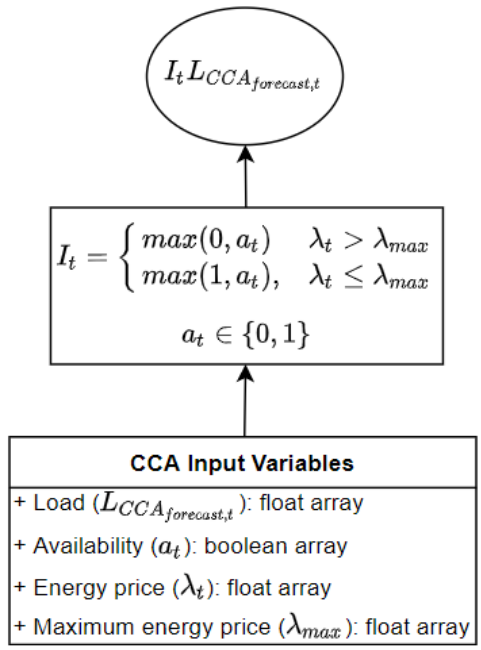

Figure 18 – Controllable Curtailable Appliances module workflow.

6.2.1. Module Requirements

Each CCA introduces two constraints to the model, one binary and one conditional constraint. There are also four input variables (a_t, $L_{CCA_{forecast,t}}$, λ_t and λ_{max}). The CCA module can also be executed outside the optimization processes, since it is a trigger module, and its results can be seen as an uncontrollable load afterwards.

6.3. Controllable Uninterruptible Appliances module

For the controllable uninterruptible appliances (CUA), the model aims to define the start time of each appliance in this group, trying to allocate their load at the cheapest time window. Once the appliance is turned on, it cannot be interrupted for the duration of the entire program due to security or quality issues. The CUA can be seen as a non-controllable load after the allocation is done.

The controllable and uninterruptible appliances require a constraint (setpoint) that ensures that the appliances can be only turned on in a specific time frame. This setpoint is the data input a_t. The CUA model introduces the following restrictions to the optimization, where the decision variable I_t is pursued:

$$\sum_{t=start}^{start+d} I_t a_t = d \qquad \text{Eq. 16}$$

$$\sum_{t=1}^{24} I_t = d \qquad \text{Eq. 17}$$

$$1 \leq start \leq 24 - \mathrm{d} \qquad \text{Eq. 18}$$

If the load starts at $start$ hour, when the hour $start + d$ (program duration) is reached, the sum of all allocations (hours turned on) must be equal to d. Where $d \in N$, I_t and a_t are binary variables ($I_t, a_t \in \{0,1\}$). The restriction represented by the Eq. guarantees that only one execution is performed a day.

The input variables a_t, d and L_{CUA} are mandatory entries to the model if a CUA exists in a prosumer/consumer residence. The output variable is I_t, but it is showed in the workflow as $I_t L_{CUA}$, but L_{CUA} is considered constant through the program duration.

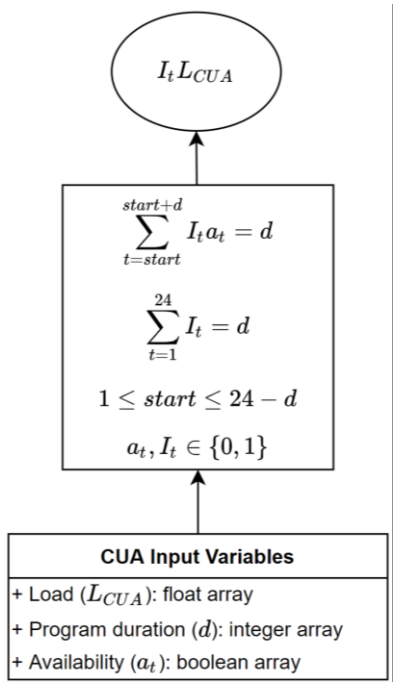

Figure 19 – Controllable Uninterruptible Appliances module workflow.

6.3.1. Module Requirements

Each CUA introduces five constraints to the model, two binary constraints, and three conditional constrains. Three input variables are also requested.

6.4. Energy Storage System module

The energy storage system (ESS) model is well described on section “Flexibility Models”, nevertheless a mathematical programing formulation is present as follows.

For ESS assets, the model provides the value of the energy that the battery delivers to the system (discharging) or extract from the system (charging) at each hour aiming to minimize the cost of energy. Such energy use is represented by the decision variable called P_t.

P_t is constrained by the maximum energy input P_C and the maximum energy output P_D, which must follow the energy efficiency limitations. The ESS is also limited by the technical minimum storage capacity ($C_{ESS_{min}}$) and maximum storage capacity ($C_{ESS_{max}}$). Should also be stressed that C_{ESS_t} depends on the value of $C_{ESS_{t-1}}$, thus, the model in not a memoryless one.

Two additional variables may be introduced if an electrical vehicle is available, the availability (a_t) and the target charge ($C_{ESS_{target}}$) that limits the charge of the battery when the EV is removed for use ($C_{ESS_{tEnd}}$).

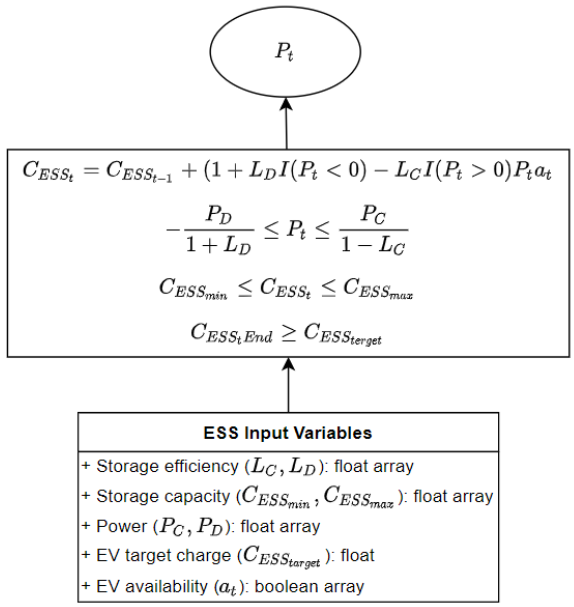

Figure 20 – Energy Storage System module workflow.

6.4.1. Module Requirements

Each ESS introduces three restrictions into the model. For the case that the ESS is an electric vehicle (EV), it also introduces a fourth restriction setting the target charge at the end of the cycle. The availability (a_t) is always set to 1 for a regular fixed ESS and is defined by the consumer/prosumer according to the connection schedule of each EV.

6.5. Energy Constraints and Objective Function

For visualization purposes, the model was divided into four modules, although this division does not reflect on the mathematical model and must be combined to compute the minimization problem.

To obtain the best result, the model must choose the values of the decision variables that minimizes the objective function below.

$$\text{Minimize}\left(\sum_{c=1}^{n}\sum_{t=1}^{24} E_{c,t}\,\lambda_t\right) \qquad \textit{Eq. 19}$$

Where c is the number of consumers/prosumers and t is the time of the day, in hours. $E_{c,t,}$ is the result of the load/generation balance equation (Figure 21), which may be interpreted as the energy requirements of each consumer c at time t. It must be noticed that the uncontrollable loads (L_{UA}) and the

generations (G) enter the equation directly, where each one of the controllable appliances adds a contribution symbolized by the summations of all appliances a. The energy constraints and objective function workflow is presented below.

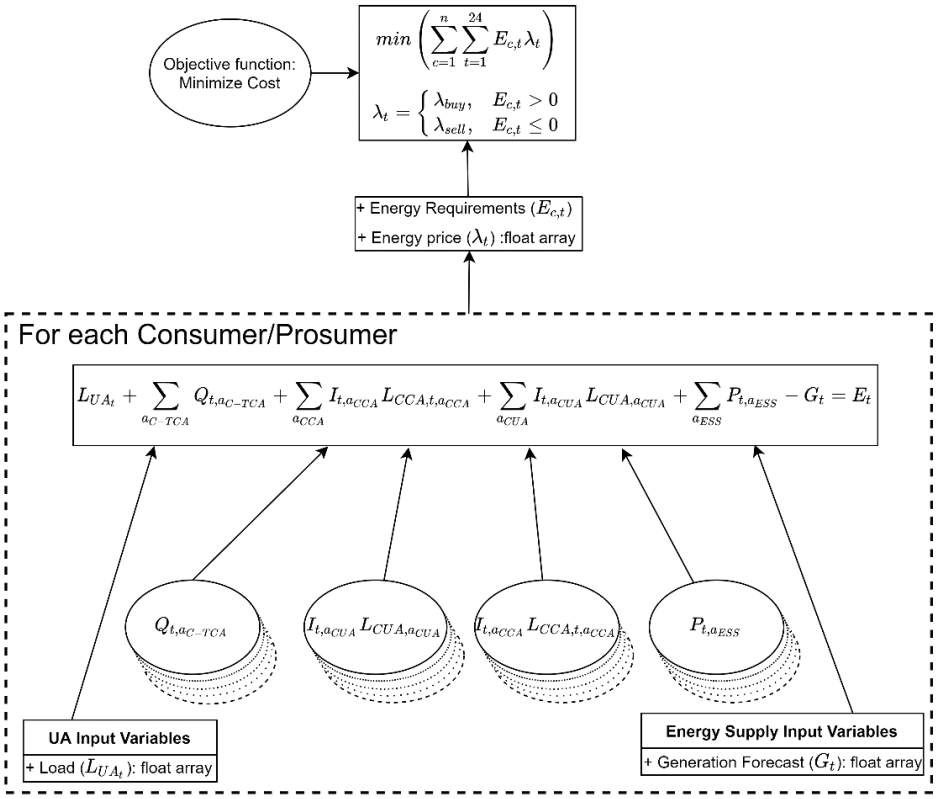

Figure 21 – Energy Constraints and Objective Function workflow.

The number of decision variables for each consumer/prosumer may be estimated by multiplying the number of each appliance type ($a_{applianceType}$) by the number of the decisions variables that each type of appliance requires ($N_{applianceType}$), times the number of hours, as described by the equation bellow.

$$N_{decisionVariables} = (a_{C-TCA}N_{C-TCA} + a_{CCA}N_{CCA} + a_{CUA}N_{CUA} + a_{ESS}N_{ESS}) \times 24 \qquad \text{Eq. 20}$$

Additionally, if the retail electricity prices to sell or buy are not the same, then five more restrictions must be added to the model.

$$\mathrm{E_t} \geq -\mathrm{M}(1-\delta) \qquad \text{Eq. 21}$$

$$\mathrm{E_t} \leq \mathrm{M}\delta \qquad \text{Eq. 22}$$

$$\lambda_{buy} - \mathrm{M}(1-\delta) \leq \lambda_t \leq \lambda_{buy} + \mathrm{M}(1-\delta) \qquad \text{Eq. 23}$$

$$\lambda_{\mathrm{sell}} - \mathrm{M}\delta \leq \lambda_{\mathrm{t}} \leq \lambda_{\mathrm{sell}} + \mathrm{M}\delta \qquad \text{Eq. 24}$$

$$\delta \in \{0,1\} \qquad \text{Eq. 25}$$

Where M is an excessively big real number.

For instance, if E_t is greater than 0, i.e., energy must be bought, then $\delta = 1$.

$$\mathrm{E_t} \geq -\mathrm{M}(1-1) \Leftrightarrow E_t \geq 0 \qquad \textit{Eq. 26}$$

$$\mathrm{E_t} \leq \mathrm{M} \qquad \textit{Eq. 27}$$

$$\lambda_{\mathrm{buy}} - \mathrm{M}(1-1) \leq \lambda_{\mathrm{t}} \leq \lambda_{\mathrm{buy}} + \mathrm{M}(1-1) \Leftrightarrow \lambda_{\mathrm{buy}} \leq \lambda_t \leq \lambda_{buy} \qquad \textit{Eq. 28}$$

$$\lambda_{\mathrm{sell}} - \mathrm{M} \leq \lambda_{\mathrm{t}} \leq \lambda_{\mathrm{sell}} + \mathrm{M} \Leftrightarrow -\mathrm{M} \leq \lambda_{\mathrm{t}} \leq \mathrm{M} \qquad \textit{Eq. 29}$$

Which implies that $\lambda_t = \lambda_{buy}$.

6.6. Controllable Load for demand-side flexibility management programs

When the system security is jeopardized, the community manager or the aggregator must have a way to securely cut load, therefore, helping to maintain the stability of the grid and providing a system service that the community may attend and get some revenues. This process is facilitated by the mathematical programing model defined previously, since it already provides all controllable loads as a possible output.

Having the scheduling optimization finished and knowing the day ahead loads at each hour, it is possible to identify which loads are the controllable ones. The controllable loads can, therefore, be offered to participate in demand-side flexibility management programs or in system security services. The maximum controllable load (flexibility) for a certain t hour can be computed following:

$$L_t = \sum_a Q_{t,a} + \sum_a I_{CCA_{t,a}} A_{CCA_{t,a}} L_{CCA_{t,a}} + \sum_a I_{CUA_{t,a}} A_{CUA_{t,a}} L_{CUA_a} + \sum_a P_t A_{ESS_{t,a}} \qquad \textit{Eq. 30}$$

Above equation implies that every controllable load may be offered to demand-side flexibility management programs, except when the availability A for each load is set to 0 by the user. In such cases, the consumers/prosumers are defining that they are not interested in any possible income from load shedding during that period for a specific load.

7. Conclusions

This report presents the FleXunity platform developments related with the Community energy assets optimization AI algorithms. Advanced Artificial Intelligence-based Community energy assets optimization algorithms are critical for the development of FleXunity platform, which will be used for managing, optimizing, and valorizing the demand-side flexibility and excess PV generation resources of energy community members (i.e.: prosumers and consumers).

These developments included mainly the formulation of mathematical models for Community energy assets optimization application. A complete mathematical model for FleXunity optimization problem has been developed and described in this report, which comprises of the operational models of (C-CTA, CCA, CUA and ESS) each type of appliance that can be controlled, other type of data inputs (such as uncontrollable loads and local generation), the global and local constraints applied to the optimization model, the decision variables, and the objective function to the optimization problem. The outcome of such an optimization process would be day ahead optimized scheduling of all appliances belonging to the consumers/prosumers, i.e., the energy needed/generated at each hour of the day. Having the scheduling optimization finished and knowing the day ahead loads at each hour, it is possible to identify which loads are the controllable ones. The controllable loads can, therefore, be traded in existing ancillary and flexibility markets.

In short, this report documents the following main achievements:

- Description of the developments of the FleXunity platform to enable the optimization of Community energy assets;

- Development of generic operational models of (C-CTA, CCA, CUA and ESS) each type of appliance that can be controlled during the optimization process;

- Description of the complete workflow for an optimization process including the key data inputs (i.e., forecasted energy prices, forecasted energy generation, forecasted energy demand, and flexible sources models etc.);

- Finally, a comprehensive mathematical model has been formulated to enable the optimization and valorization of the demand-side flexibility and excess PV generation resources of energy community members (i.e.: prosumers and consumers).

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