Report on algorithms to unlock flexibility in electric distribution grids

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[1] PU = Public
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Summary

This document describes the research on flexibility algorithms carried out in the ebalance-plus project.

First (chapter 2), a review and analysis of current state of the art is described, addressing local flexibility markets and different approaches regarding ancillary services mechanisms considering the target assets and control strategy.

Moreover, one of the main contributions of this research (chapter 3) is an **official formulation** of the flexibility steering signals (control signals that activate the flexibility in the customer premises) considering current approaches (OpenADR and USEF) and fair principles between the energy customer and the future energy aggregator.

In the context of ebalance-plus project, the flexibility scenarios (use cases) addressed in the corresponding demo sites (Spain, Italy, France and Denmark) are formulated and described in chapter 4.

Finally, in chapter 5, to support the energy flexibility estimation and management three different approaches using artificial intelligence are described.

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Table of Contents

This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement N°864283

Table of tables

Table of figures

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Abbreviations

AC	Alternate Current
AI	Artificial Intelligence
BESS	Battery energy storage system
BPMN	Business Process Model and Notation
BRP	Balance Responsible Party
BSP	Balance Service Provider
CMSP	Congestion Management Service Provider
CMU	Customer Management Unit
CRO	Common Reference Operator
CSP	Capacity Service Provider
DA	Day-ahead
DBS	DC Bus Signaling
DC	Direct Current
DER	Distributed Energy Resources
DERMU	DER Management Unit
DR	Demand Response
DSO	Distribution System Operator
EC	European Commission
EMP	Energy Management Platform
EMS	Energy Management System
ESS	Energy Storage System
EU	European Union
EV	Electric vehicle
FCR	Frequency containment reserve
FF	Flexibility Function
HVAC	Heating Ventilation and Air Conditioning
IEA	International Energy Agency
ISGAN	International Smart Grid Action Network
ISP	Imbalance settlement period
LFM	Local Flexibility Market
LMP	Local Marginal Price
LSTM	Long Short-Term Memory

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LVGMU	Low Voltage Grid Management Unit
MDR	Metered Data Responsible
MIP	Mixed Integer Programming
ML	Machine Learning
MPC	Model Predictive Control
MU	Management Unit
MVGMU	Medium Voltage Grid Management Unit
OASIS	Organization for the Advancement of Structured Information Standards
OCP	Optimal Control Problem
OpenADR	Open Automated Demand Response
P2P	Peer-to-peer
PDF	Probability Distribution Function
PEM	Packetized Energy Management
PID	Proportional Integral Derivative
PV	Photovoltaic
RES	Renewable Energy Source
RMSE	Root Mean Square Error
SMUD	Sacramento Municipal Utility District
SoC/SOC	State of Charge
TCL	Thermostatically controlled loads
ToU	Time of Use
TSO	Transmission System Operator
USEF	Universal Smart Energy Framework
VEN	Virtual End Nodes
VPP	Virtual Power Plant
VTN	Virtual Top Nodes

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1 Introduction

1.1 Energy flexibility challenges and needs

The European Commission (EC) commitment of decreasing carbon emissions by 40% (of 1990 levels) by 2030 and reach climate neutrality by 2050 has led to a continue increase of the renewable energy sources (RES) share in the electricity sector. The uncertain and uncontrollable nature of these resources brings **new challenges** [1]:

- The variability of RES challenges a reliable grid operation of future electricity systems as the grid needs a balance between supply and demand. This variability also challenges supply security, requiring higher capacity back-up for low RES generation periods [2].
- It potentially leads to an increase in the costs of the system maintenance and operation which can be passed on to end-users, worsening energy poverty situations.

To solve these issues **new sources of flexibility** should be used. According to The International Smart Grid Action Network (ISGAN), flexibility can be defined as the ability of electric systems to manage change [3]. More detailed definitions are given by [4] and [1], defining flexibility as the ability to modify the expected consumption and/or generation based on a signal.

Flexibility assets include controllable loads, power generation (renewable and non-renewable) and storage assets [5], [6]. The first one is denominated demand response ({Citation}DR) and can be also defined as the *"...action taken to reduce electricity demand in response to price, monetary incentives, or utility directives so as to maintain reliable electric service or avoid high electricity prices"* [7].

DR together with energy storage could provide flexibility services efficiently [8] and may directly contribute to the resilience of future low-carbon electricity systems (Anaya & Pollitt, 2021b; Heffron et al., 2021). [3] also mentioned the need of flexibility highlighting that DSOs should have new flexibility mechanisms to manage the grid and enable the integration of RES avoiding a negative impact in the service reliability and quality.

Flexibility can be traded in two ways: within the same local network (peer-to peer) or at large scale. In the peer-to peer (P2P) approach, flexibility is traded at the agreed price with no need of intermediate actors. On the other hand, the second approach requires flexibility markets to trade flexibility at a large scale [5].

In order for a flexibility market to exist, there must be both consumers of flexibility (DSOs/TSOs) and providers of flexibility. Furthermore, to allow all consumers to participate in the market without discrimination, flexibility must be managed by market rules.

To achieve this, regulation is key. Regarding the current situation in Europe, the EC allows DSOs to acquire flexibility using a market-based approach in coordination with TSOs [9], especially for local congestion management, which is the most common

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application for flexibility services [5]. Some recommendations to update the regulation are compiled by [3]:

- Implementation of the European Directive 2019/944 [9], article 32 in the national regulations.
- Regulation of the interaction between new flexibility mechanisms and existing markets.
- Integration of access and connection criteria and the different flexibility mechanisms.
- Review of the remuneration framework for DSOs to develop incentives for the adoption of flexibility services and encourage efficient development of the network.

The role of the Aggregator can be also helpful for small flexibility providers to participate in the market, lowering the risk in case an specific asset is not available [3], [6]. Furthermore, [5] emphases the need of a standard methodology.

[10] identified the **main flexibility challenges** and grouped them in three groups as follows:

- **Challenges to RES integration**: High entry costs, weak participation incentives, and high risk perceived by TSOs/DSOs
- **Challenges to TSO/DSO coordination**: technical and institutional barriers to information sharing and collaboration between TSOs and DSOs
- **Challenges to market design**: Alignment of market arrangements and product specifications

Additionally, a local flexibility market has requirements such as identifying the flexible resources in the grid, providing hardware and software infrastructures, and determining the user engagement method [8].

1.1 The ebalance-plus ecosystem

The solutions to be developed within the ebalance-plus project are built around the major component of the project – the ebalance-plus energy management platform. The hierarchical approach followed in the project allows involving different smart-grid innovations (smart production, storage, and consumption technologies, etc.) and to realize distributed and scalable energy control. The approach exploits the actual topology of the energy grid and makes use of computational elements (management units - MUs) that are located on the joints of the grid topology branches, to be closer to the monitored and controlled assets, enabling the decision-making process to be local. These MUs are located on different levels of the grid and manage all the lower-level management units, but also additional elements, like sensors and actuators, located in their branch (see Figure 1.1). Similar to a fractal, depending on the level of the considered MU, the monitored parameters and control tasks are the same, but they differ in the scale. This allows developing generic algorithms that can be deployed on the MUs in the smart grid in order to realize many different tasks. This allows monitoring flexibility-related parameters on different levels of the grid and applying local and appropriate actions to unlock the available flexibility.

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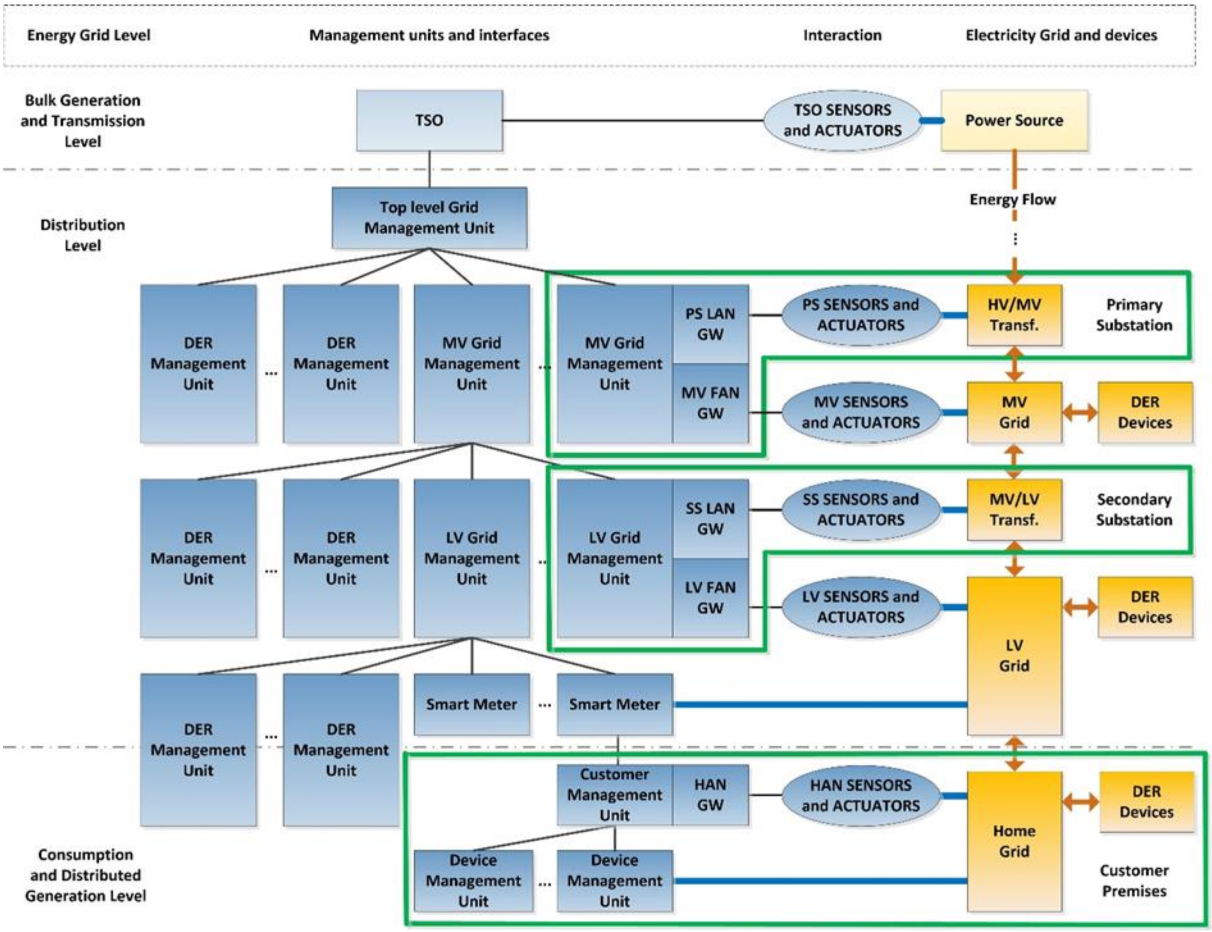

Figure 1.1 The naming and distribution of management units within the energy grid

The flexibility algorithms proposed in the context of ebalance-plus take advantage of the hierarchical architecture and the bidirectional data exchange to propose a trust environment where the energy flexibility can be measured and managed by all the stakeholders and system users as it is done currently with the power and energy data in power systems.

1.2 The ebalance-plus energy balancing platform

The management units are parts of the distributed energy management platform. These exchange the data being the measurements as well as the control signals to monitor and control the grid assets. The data exchange is realized based on the middleware and the energy management components (like the algorithms) reside on top of it. Each management unit expresses the similar architecture of the energy management platform, but the exact set of algorithms and other components may differ depending on the specific deployment. The generic architecture of the Energy Management Platform (EMP) is shown in Figure 1.2 - within the presented management unit the EMP consists of four components: the GUI to interact with the user, the EMP Coordinator that manages all the other EMP components, and two components that perform the energy management related to energy flexibility and resilience. All these components exchange data using the middleware. They all also interact with the grid assets (via measurements and control signals) using adapters (that are not reflected in this figure).

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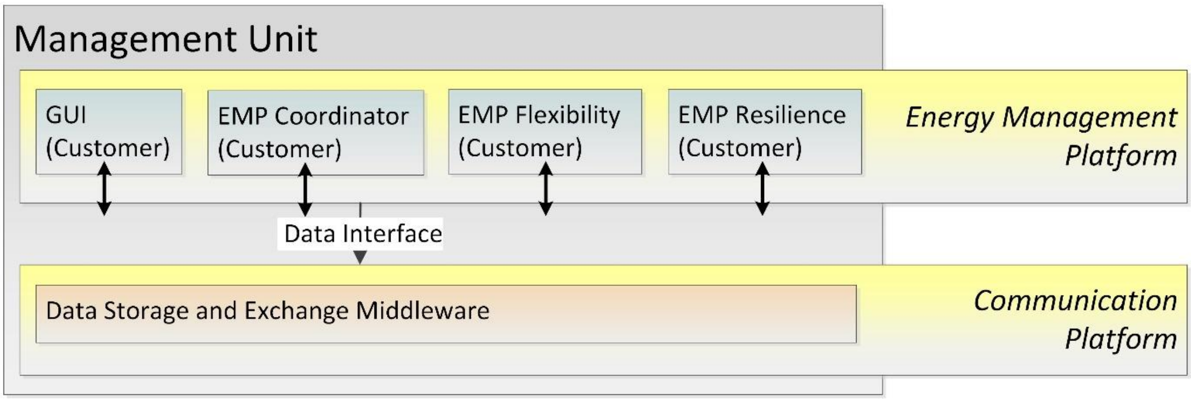

Figure 1.2 The generic architecture of the ebalance-plus Energy Management Platform

The details on the Energy Management Platform are provided in ebalance-plus deliverable D4.3.

2 State of the Art

In this section the state of the art of solutions and mechanisms related to flexibility-based market is presented, i.e., local flexibility markets, peer-to-peer and ancillary services. The first step to develop new algorithms or mechanisms for energy or flexibility management is to identify the current market needs. The ebalance-plus flexibility algorithms consider the state of the art to align the energy management platform with current trends but preserving the market-agnostic approach to adopt future changes in regulations and make it as generic as possible to satisfy the needs or current and future market players (energy aggregators and balance responsible parties). Flexibility-based energy markets evolve quickly as they have been identified as strategic for the decarbonisation and energy transition of Europe, thus the timeline of information presented should be considered.

2.1 Local energy flexibility markets

Local Flexibility Markets (LFMs) are the means through which it is possible to unlock the flexibility of Distributed Energy Resources (DERs) at the distribution level [11]. Indeed, in the last years the aggregators of large portfolios of small scale DERs have started to participate into energy markets [12]. Many research projects studied the way to provide such energy flexibility in buildings and smart energy grids, mainly from the electrical engineering of energy systems and energy storage perspectives. Typical technical solutions of energy flexibility include for example the control of heat pumps, district heating, HVAC, photovoltaic and lighting systems with energy flexibility sources coming from batteries, water storage, thermal storage in the building material [12].

The LFMs appears to be one of the better flexibility solutions in the EU framework, indeed the EU advices to the Distribution System Operator (DSO) to acquire the necessary flexibility through market-based solutions [13]. According to [14], the LFMs will be able to operate in parallel with the pre-existing energy markets and in this context, both aggregator and DSO will have to negotiate the flexibility [14]. In [11] an overview of how an LFM would work is provided. First of all, it is focalized on the need of a reliable smart meter infrastructure; moreover in [11] it is also underlined how in the

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current regulatory framework, the DSO flexibility is not incentivized to adopt flexibility operation, so the regulatory framework needs to be changed. It has been shown how, to operate efficiently the distribution network, the flexibility services can be required to the LFM when it necessary to solve some issues.

To manage DERs, aggregators need particular optimal management strategy; furthermore, they need to estimate the supply curve, also to quantify the costs of the different services [11]. The DSO requires a probabilistic assessment of the state of the distribution network, so that a cost function through which operate can be obtained. In [11] the market clearing mechanism are analysed, they are referred to the flexibility energy markets through capacity limitation services, demonstrating that the pay as bid, uniform pricing and Vickrey-Clarke-Groves [15] auction mechanisms do not meet the critical economic properties for these markets. For this issue, an alternative mechanism is proposed; it provides a fair compromise between budget balance, compatibility of incentives and individual rationality [11]

As expressed in [16], LFMs can help to monitor energy flows, motivate changes in prosumer energy supply and demand, achieving local energy balance, and optimization of electricity flows. In [16] a decentralized flexibility market, based on blockchain has been proposed; it allows to the small prosumers to exchange in a peer-to-peer way their flexibility, in terms of load modulation, concerning the energy baseline profiles. An energy flexibility token has been defined to digitize prosumers flexibility, allowing to be exchanged on the market as asset and smart-contract for decentralized market operations, including features such as placement of flexibility offers, trading session management and different energy flexibility regulations [16]. The proposed energy flexibility market, blockchain based, allows participants to exchange their flexibility in a P2P way. It facilitates the interaction of two types of market participants: both flexibility buyers and sellers. The aggregators, the DSO and TSO can be indicated as flexibility buyers, while the prosumer can be seen as flexibility sellers, because they adapt their energy profile so to offer flexibility [16].

Local markets provide an environment in which prosumers can interact with each other, either directly through peer-to-peer (P2P) markets, or indirectly through community-based markets [17]. In the hierarchical approach proposed in [17] for local energy and the exchange of flexibility between prosumers in distribution networks, the prosumers are able to exchange energy via P2P mode and negotiate flexibility in the local energy market to maintain the constraints of the distribution network. The proposed method allows to the prosumer to manage own resources and to participate to a P2P market. The local market operator manage the P2P market for the exchange of energy among the prosumers and collaborates with the DSO to distribute the flexibility provided by the prosumers [17].

There are several obstacles to fully exploiting the flexibility potential of small prosumers, they have been summarized in several papers [14], [16], [18], [19]. Such obstacles can be represented by technological barriers, that allows to shift from the traditional market to the decentralized one. They can be resumed in: economic and regulatory barriers, which consist of actual business models that are unable to give adequate value to the flexibility of small-scale prosumers and, at the same time the current regulatory framework needs to be adequate; organizational barriers affecting user involvement [16]. Moreover, [14] underlines that baseline services in local flexibility markets are not compatible with the active participation of DERs to energy

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markets, introducing unnecessary uncertainties, administrative burdens, risks and potential conflicts of interest between different stakeholders. While the obstacles that occur in the implementation of the flexibility market shown in [19]refer to standardization problems; starting from this issues, in [19] a hybrid market model comprising elements of a local flexibility market and a local energy market was developed.

LFM are already implemented in several European countries, such as the United Kingdom (UK), Germany, the Netherlands, Sweden, or Norway. In addition, there are some local market platforms currently in use, for example, Piclo Flex [20], GOPACS [21] and NODES [22]. In order to find different design alternatives, several European H2020 research projects like Integrid [23], EUniversal [24], CoordiNet [25] and INTERRFACE [26], among others, are exploring different solutions [3].

In the UK five DSOs have implemented four different flexibility services in the market. These services are [3]:

1. Sustain**:** System support service under normal network operating conditions.
2. Secure**:** System support service when the safety margins have been exhausted.
3. Dynamic: System support service when a failure has occurred in any element.
4. Restore: System support service when a service restoration is required.

To sign a flexibility contract, the DSOs have developed procedures for comparing the value provided by each offer received against the traditional network reinforcement alternative. To streamline and optimize the contracting and operation process of flexibility services, they use two platforms: Piclo Flex [20] for the publication of requirements and verification of offers, and FlexiblePower API [27] for the automation of dispatch and settlement of services [3].

2.2 Energy flexibility for ancillary services

In this section, some of the existing algorithms for procuring energy flexibility of end-users for grid services are briefly described. The algorithms and studied cases are chosen such that different flexible resources, ancillary services, and control strategies are reviewed.

2.2.1 Balancing services

In the last years the use of flexibility resources to provide balancing services has become one of the first issues of electric energy markets. Various uses to exploit flexibility resources for balancing services are described below.

Balancing markets must not be considered individual energy markets, but as part of different kind of electricity markets, like the day-ahead energy market or the short-term or real-time electricity markets. In particular, the links among the short-term markets provide alternatives for the commercialization of energy flexibility and motivate the bidding strategies of balance service providers [28]. Moreover, to improve the performance and competitiveness of balancing markets, the European Union introduced a common market for balancing energy, that is usually traded with the balancing capacity [29], [30]. This autonomous balancing energy market allows the participation of many providers that are configured as Balancing Responsible Parties

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(BRP) and other Balancing Service Providers (BSP) with available flexibility that can submit voluntary offers on demand. In this context, several authors have proposed innovative ways for bidding, scheduling, aggregation of customers, estimation of flexibility, etc.

Innovations in bidding strategies

In [30] a model of agents' interdependent bidding strategies in the balancing capacity and energy markets is proposed, where machine learning algorithm are employed, in particular two collaborative reinforcement-learning algorithms are used. The results of the proposed model show significant efficiency gains in the balancing energy market, introducing voluntary bids even in highly concentrated markets and at the same time, offering a new value to short-term flexibility providers.

In [31] a real time bid-less market is proposed; it is useful to eliminate the barriers for small users, both consumers and producers to provide services to the system. Starting from the DA energy market results, if no balancing services are required, the price is that determined from the DA market, on the contrary the TSO intervenes to minimize the cost for the balancing power and determining the necessary power from the market to provide the entire services

Innovations in aggregation of customers

In [32], [33] a mixed-integer distributed approach to aggregation of prosumers to provide balancing services has been proposed. It considers a number of prosumers aggregated by a service provider to be able to offer a defined flexibility degree and to make available a power variation in a defined time interval, after that the TSO (or other grid operator) requires explicitly such variation.

In [33] it is defined how the service provider can distribute in an optimal way the flexibility requests to the prosumer and at the same time provide the service requested by the TSO. The provision of balancing services to the TSO is analysed, with particular attention to the provision of services through an aggregation of prosumers rather than a big industrial entity. The main aim is to elaborate an algorithm to coordinate a number of users as big as possible, satisfying the flexibility requests of the TSO. The proposed strategy is based on a Mixed-integer linear programming formulation of the problem and on its solution using distributed computations. The implemented approach is scalable since it decomposes the overall problem into problems that use decision variables related to the prosumers, it provides a solution to the privacy-preserving issue because the users have not to share their daily behaviour.

In [34] a review on the balancing flexibility in terms both of flexibility products and flexibility market design is carried out. Moreover, it underlines how it is possible to analyse the energy flexibility for balancing services from different point of view, that can be those of the aggregator or balancing service provider, of the distribution or transmission grid operator.

New mechanisms and approaches to integrate DER and EV

Until today, the flexibility services that can be offered to the TSO for power balancing are provided through big thermal power plants, hydro power plants or DR of big

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consumers [34]. It depends on the dimension of requested power balancing services. At the same time, the DSO can provide flexibility services for local balancing using Distributed energy resources, connected at the distribution grid [34].

Considering the TSO, although the provision of services is now consolidated at this level, in all the world new products are of interest for new and existing energy market. In the USA energy market, for instance, new ramping capacity products from the existing traditional suppliers are being considered, with the main objective to integrate them into the existing dispatching procedure [34]. In many other countries, such as in Italy, the DSO could provide flexibility services for the transmission grid using DER. In this context, the coordination between TSO and DSO become very important, in particular to avoid any kind of problem to the distribution and transmission grid. The DSO is therefore called upon to provide new functions and integrate them into the existing technical and regulatory scenario. In fact, as described in [35], in the Californian electricity system, flexibility was proposed in terms of fast ramping capacity, that could be supplied in 5 min, that is only provided from the supply side at the transmission grid.

The [36] proposes the use of EV to provide flexibility ramping in markets. In this work, EV participation is analysed as standalone aggregated EV flexibility providers, or by cooperating with traditional generators to improve their ramp capabilities. On the other hand, in [37] the integration of electric vehicles into the distribution network is considered to provide flexibility services, highlighting the possible barriers encountered.

Innovations in aggregation mechanisms

In [38] an optimization model for a load aggregator has been proposed; in particular, the aggregator is involved both in the electricity energy market and in the regulation capacity market. The aim is to minimize the total cost allocating the consumer flexibility opportunely among the different markets, managing the resources on the distribution grid and coordinating opportunely the TSO and DSO operation.

In general, flexibility demand for balancing services does not depend on the geographical location of the resource, so it could be interesting to defer the investments using the services provided by the DSO at the distribution grid and at the same time using the advantage of the local market [34]

The local market operator in [39], in addition to the energy profiles, receives the different flexibility offers from the aggregators and at the same time it receive flexibility requests from DSOs and BRP. Then the DSO uses a local dispatching strategy to solve the remaining security network issues.

2.2.2 Providing balancing services by thermostatically controlled loads (TCLs) using direct load control

A method for utilizing the flexibility of a group of TCLs for providing balancing services is suggested in [40]. The method is based on direct load control and is presented in Figure 2.1. The aggregated power ($P^{agg}(t)$) of all TCLs are compared with a defined baseline ($P^{base}(t)$) for each time interval. The difference between aggregated power

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and baseline ($\delta(t)$) is compared with the required flexibility for the balancing service at that moment ($r(t)$). If $\delta(t) < r(t)$ more electricity should be consumed and if $\delta(t) \geq r(t)$ less electricity should be consumed. Priority stack controller is used to determine which TCLs should be ON or OFF to increase or decrease energy consumption. The TCLs whose temperature is close to the minimum temperature have higher priority to be turned on and TCLs with temperatures close to the maximum temperature have higher priority to be turned OFF.

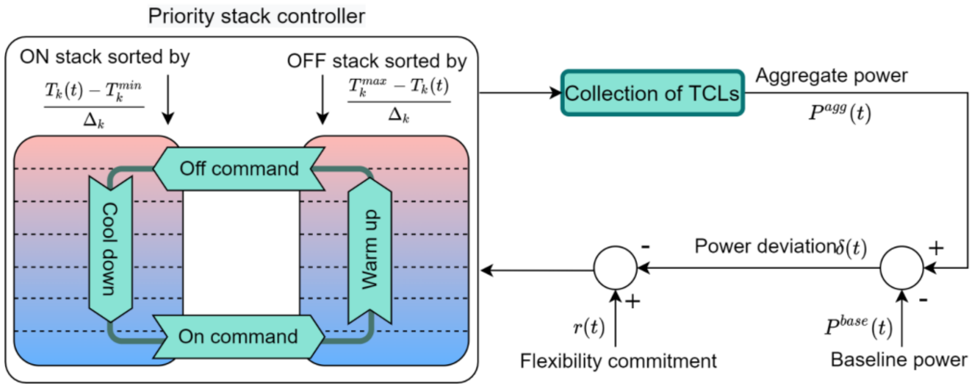

Figure 2.1 Schematic representation of the proposed direct load control approach for providing balancing services.

2.2.3 Procuring energy management and frequency control services from energy storage systems (ESSs)

The fast dynamics of ESSs and their capability of both consuming and generating energy allows us to use them as frequency containment reserve (FCR). In [41], the authors propose a methodology to assess the techno-economic performance of photovoltaic household prosumers that jointly provide self-consumption enhancement and FCR. Battery and supercapacitor are used as ESSs. A simplified block diagram of the proposed method is presented in Figure 2.2.
As shown in Figure 2.2, the building energy management system receives information about output power of a photovoltaic (PV) panel, energy consumption of the building, and status of the ESSs and generates signals for controlling the battery and supercapacitor. On the other hand, FCR provision system measures the frequency continuously. If the frequency deviates from a predetermined dead band, the FCR provision system creates control signals for battery and supercapacitor considering the prequalified FCR power and special characteristics of the battery and supercapacitor. Since the aggregated control signals obtained from energy management and FCR service may result in violations from maximum or minimum state of charge (SOC) limits of the battery or supercapacitor, a SOC management system is designed to control the SOCs and makes changes if necessary.

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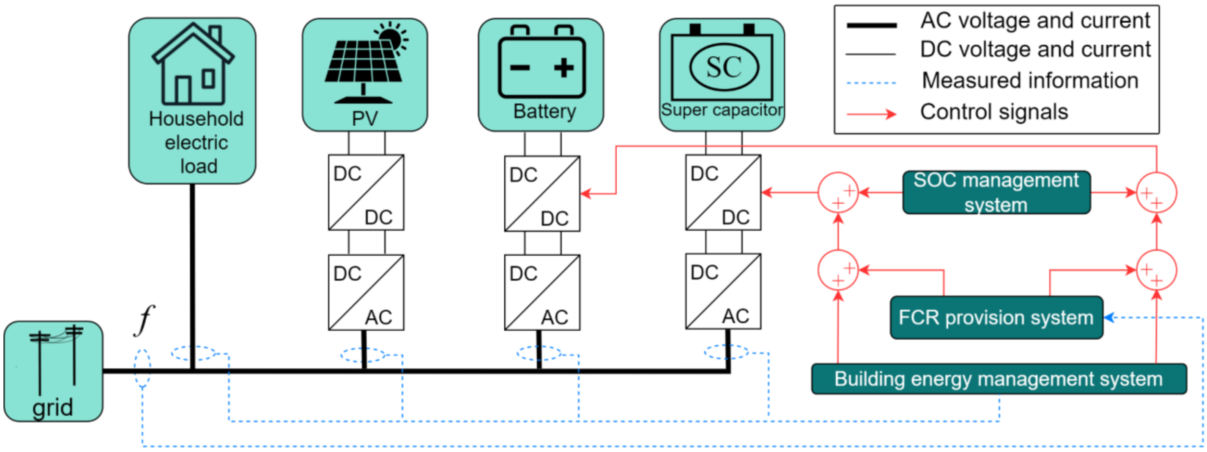

Figure 2.2 Block diagram of the proposed method for utilizing the flexibility of ESSs for FCR service

2.2.4 Aggregation of electric vehicles (EVs) for providing primary frequency control service

In [42], the authors propose a method for utilizing the flexibility of a group of EVs for primary frequency control through an aggregator. The block diagram of the introduced method is depicted in Figure 2.3. The main difference between the proposed method for EVs and conventional power plans is defining the participation factor K_i for each EV i. This factor determines how ready an EV is to provide service for the grid and depends on the operation mode of the EV i.e., charging, or idle mode, and SOC of the battery. As shown in Figure 3, when the EV is in charging mode, the value of the participation factor is small for low and high SOCs and equal to one for other situations. If the EV is in idle mode, the participation factor is small for low SOCs and then is equal to one in other cases. The battery charger controller block is responsible for satisfying the upper and lower bounds of consumed power by EVs.

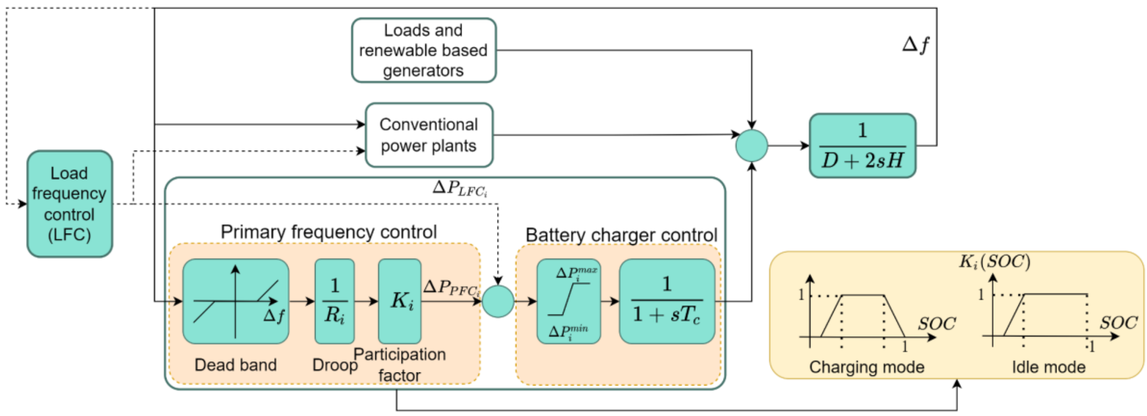

Figure 2.3 Process of utilizing EVs' batteries for primary frequency control ancillary service.

Similar approaches are suggested in other studies to use the flexibility of EVs for frequency-related ancillary services. In [43]–[45] fuzzy logic is used to find the optimal control strategy for EVs that provide primary and secondary frequency control services. In [46] a robust mixed H_2/H_∞ controller based on static output feedback is designed to support the LFC services along with different uncertainties. In [47] two controllers are proposed for using the aggregation of EVs for primary frequency control in an industrial

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microgrid equipped with PV panels and wind farms. This method considers different charging profiles, the SOC of electric vehicle batteries, and a varying number of electric vehicles in an electric vehicle fleet. A non-linear model-free approach is introduced in [48] to use the flexibility of EVs for secondary LFC in standalone micro-grids.

2.2.5 Procuring the flexibility of hybrid PV/battery systems for congestion management in the distribution grid

CONSORT project is one of the successful examples of using price-based methods for congestion management in distribution grid using the flexibility of PV/battery systems [49]. This project has been implemented in Bruny Island (Australia). The schematic representation of the introduced algorithm is presented in Figure 2.4. Grid and weather data are collected by a cloud server and load patterns are forecasted every 5 minutes. The optimal power flow (OPF) problem is solved in the server covering next 24 hours using load forecasts. From this solution, network feasible real and reactive powers are sent to each customer as a request alongside the relevant standing locational marginal prices (LMPs). Energy management systems (EMSs) solve the customer problems by optimizing their DER use in response to the LMPs and support power requested by the cloud server. Their best response is sent back to the server, where the LMPs are then updated to reflect the changes to the network use. The negotiation iterates between end-users and the server until the algorithm identifies convergence to a level of support where the network's constraints are satisfied, and customers are happy with the offered LMPs.

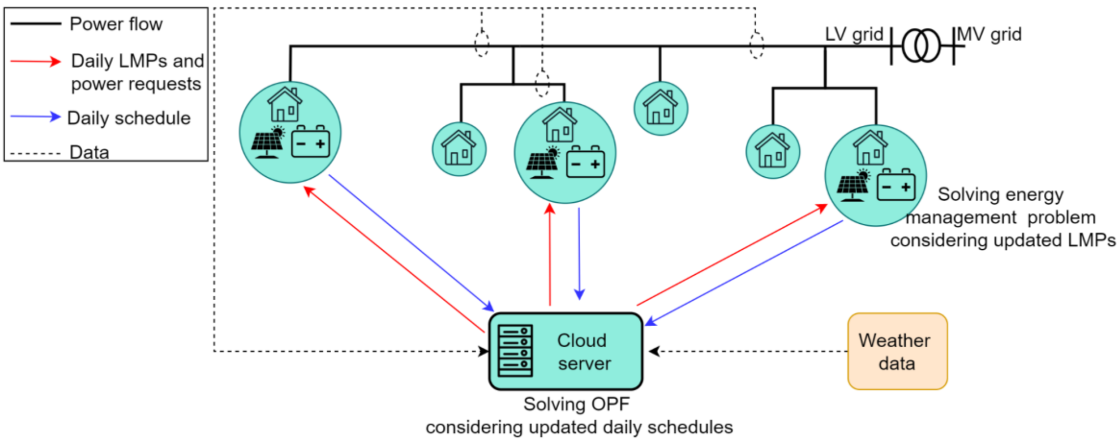

Figure 2.4 The proposed market-based mechanism for congestion management in the CONSORT project

2.2.6 Utilization of EVs' flexibility for congestion management in the distribution grid

An algorithm is proposed and evaluated in [50] to use the flexibility of EVs for congestion management. The Block diagram of the proposed algorithm is presented in Figure 2.5. A market is defined in this method that operates under the supervision of DSO. This market penalizes the congestion in the grid and creates shadow prices (monetary value assigned to currently unknowable or difficult-to-calculate costs in the

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absence of correct market prices) for end-users that force them to reschedule the EV charging plans such that the grid congestion problem is solved.

According to the proposed method, the EV owner selects the desired charging requirements, and the EV controller generates the charging schedule based on, e.g., the charging least-cost strategy, the dumb charging strategy, etc. The charging schedule is sent to the fleet operator. The fleet operators aggregate the charging schedule from their contracted EV owners and submit the aggregated charging schedule to the DSO. The DSO runs load flow calculation and sends the results to all fleet operators. If congestion exists, the fleet operators submit the charging schedule to the market operator. The Market operator sends the shadow price to the fleet operators, and then the fleet operators re-submit the charging schedule to the Market operator until the shadow price is converged. The fleet operators send the shadow price to all the EV controllers. The EV controller updates the charging schedule based on the new shadow prices. This process is repeated until the congestion is eliminated in the planning period. The bids that do not cause any congestion are submitted to the electricity spot market.

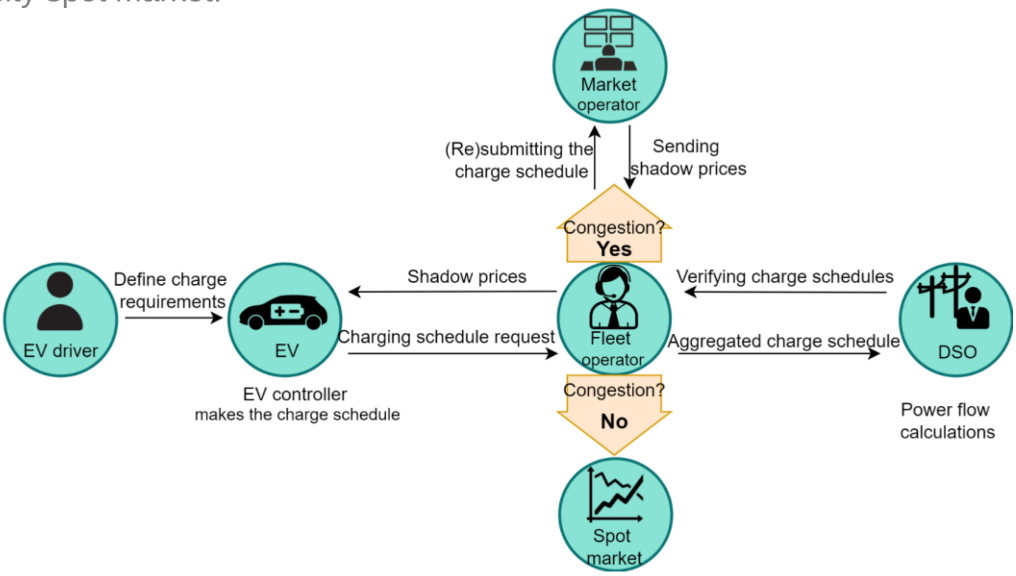

Figure 2.5 Proposed algorithm for congestion management using EVs

Congestion management using EVs is investigated in other studies, too. In [51] power distribution factors are used to determine the amount of energy that a specific EV should contribute to alleviate the congestion in a line. In [52] a decentralized control strategy is proposed for the optimal scheduling of the energy charging of a fleet of EVs while considering congestion management. The scheduling problem aims at ensuring a cost-optimal profile of the aggregated energy demand and at satisfying the operational constraints of power grid components and EV locations. The dynamic subsidy is a locational price paid by the DSO to its customers to shift energy consumption to designated hours and nodes. A dynamic subsidy method is proposed in [53] for congestion management in the distribution grid in presence of EVs and Heat pumps.

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2.2.7 Flexibility Function method for price-based flexibility procurement

A methodology is proposed by Rune, et al. [54] to estimate the energy flexibility of buildings as a dynamic function called the Flexibility Function (FF). The FF receives penalty signal data in past time intervals and external variables such as ambient temperature and gives the amount of energy flexibility we can get from the building for each penalty signal. Three different penalty signals can be defined as follows:

- Real-time CO2. If the real-time (marginal) CO2 emission related to the actual electricity production is used as a penalty, then, a smart building will minimize the total carbon emission related to the power consumption. Hence, the building will be emission efficient.
- Real-time price. If a real-time price is used as a penalty, the objective is to minimize the total cost. Hence, the building is cost-efficient.
- Constant. If a constant penalty is used, then, the controllers will simply minimize the total energy consumption. The smart building is, then, energy efficient.

The mathematical representation of FF is as below:

$$Y_t = \sum_{i=1}^{\infty} h_t(\theta)\lambda_{t-i} + R_t$$

Where Y_t is the estimated load in response to penalty signal λ_t. h_t is the impulse response function, θ is the decision variable, and R_t represents the non-responsive load. Historical data are used to determine the parameters of the flexibility function.

The FF can be very useful for generating suitable price signals for procuring a desirable amount of flexibility in indirect price-based control methods as depicted in Figure 2.6.

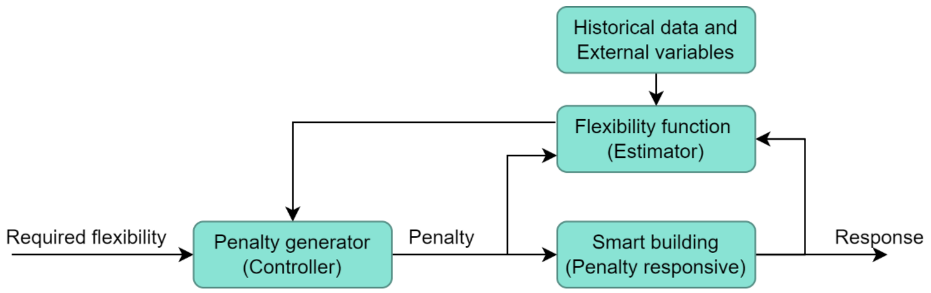

Figure 2.6 Application of FF in procuring flexibility

2.2.8 Packetized energy management

Packetized energy management (PEM) is a recently introduced scheme that defines a framework for interaction between aggregators and end-users for procuring flexibility services from the distribution grid level [55]. The basic structure of this framework is depicted in Figure 2.7(a). At the end-user level, the state of each controllable device is observed, and the ON/OFF status of the device in next time interval is determined. If the device is supposed to be ON in next time interval, an access request is sent to the aggregator. The aggregator collects all requests received within a specific time interval, e.g., 10 sec, and informs the availability of flexible loads to the DSO. DSO estimates the system state in the next time intervals considering the requests received from aggregators and sends dispatch signals to aggregators. The aggregator decides

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about accepting or rejecting the access requests. If rejecting the access request leads to violating the operational constraints of a device, the end-user can opt out of the PEM scheme.

One of the main features of this scheme is the proposed method for deciding about sending the access request at the end-user level. Instead of using complicated optimization approaches, it is suggested to decide about the ON/OFF status of the device using the probability distribution function (PDF) of sending access requests. An illustrative example of this method for a swimming pool heat pump application is depicted in Figure 2.7(b). However, the method can be applied to other controllable devices in buildings. At each time interval, a random number, e.g., A^1, A^2, B^1, and B^2, is generated. Then, considering the water temperature, this random number is compared with the PDF curve. If the generated random number is below the PDF curve the access request signal will be sent to the aggregator. As shown in Figure 2.7(b), when the water temperature is low (T^A), the access request signal will be generated for both random numbers A^1 and A^2, but when the water temperature is high the access request signal will be generated only for random number B^1. Using this approach, the probability of sending access requests decreases as the water temperature increases. The PEM scheme does not consider electricity price in the decision-making process, so it is not cost-efficient, however, it is easy to implement, and efficient in terms of procuring flexibility services for the grid.

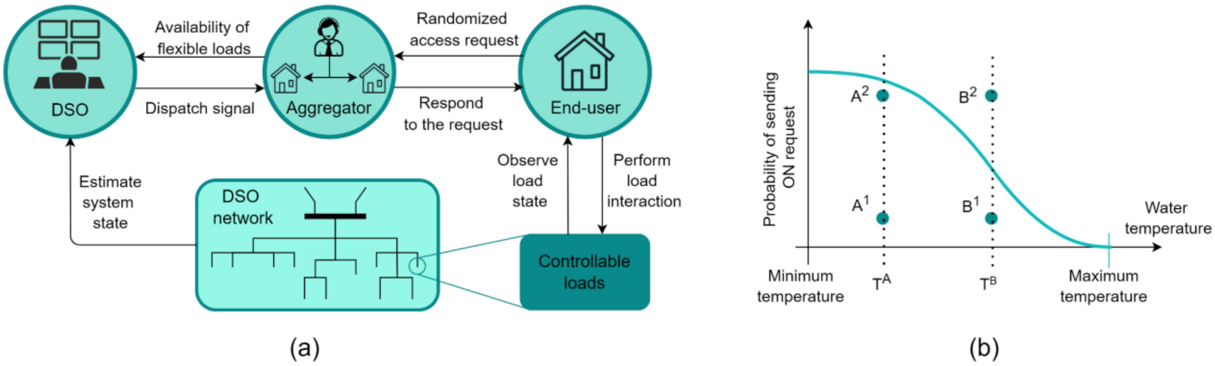

Figure 2.7 a) The required framework for implementing the PEM approach and b) the principle of the PEM

2.2.9 Market-based flexibility trading in +CityxChange project

In the +CityxChange project (H2020 Grant Agreement No. 824260), a market-based platform is proposed for trading flexibility among end-users or between end-users and DSO [56]. In this method, the DSO can be a market operator or a market player. In case the DSO is the market operator, it can monitor the grid continuously and allows flexible transactions among market players i.e., end-users of aggregators, that help solve grid issues. If the DSO is a market player, a local market operator manages the local flexibility market (LFM). In this case, the DSO can solve grid congestion or voltage regulation issues in the local grid by sending flexibility requests to the LFM as shown in Figure 2.8(a). The structure of this market is similar to the day-ahead market where buyers and sellers of flexibility can submit their bids and offers, and the market is cleared by the market operator using a uniform pricing method. The market clearing process is illustrated in Figure 8(b). More details about the proposed market structure can be found in the Deliverable D1.1 [8] and [56].

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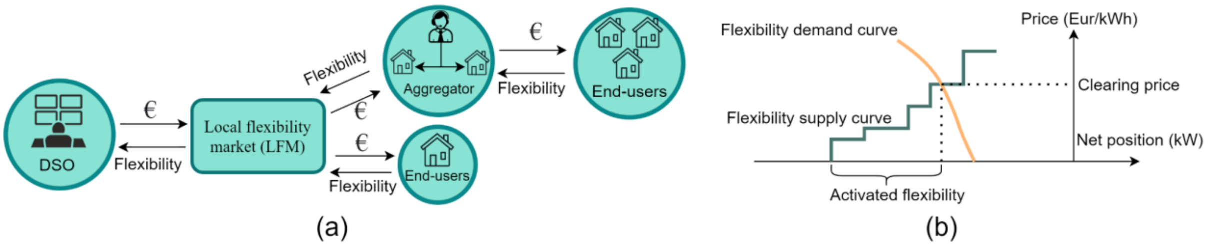

Figure 2.8 Project +CityxChange a) proposed market framework for trading flexibility, b) market-clearing method

2.2.10 A flexibility market alongside existing markets proposed in the NODES project

In the NODES project, it is suggested to have a central flexibility market in parallel with the day-ahead and reserve market [57]. A schematic diagram of this system is presented in Figure 9. Aggregators, retailers, and service providers participate in this market on behalf of end-users, and DSO, TSO, and BRPs are the buyers of flexibility. The flexibility bids in this market are tagged locationally which gives them to use for both central and local flexibility services. The TSO can use the flexibility bids for providing balancing ancillary services and the DSO can utilize local services such as distribution congestion management. BRPs can also use this available flexibility to reschedule their portfolio and retrade flexibility with other BRPs. More details about the proposed approach can be found in the [8], [57]

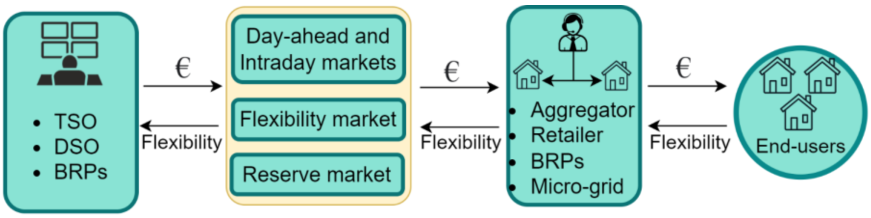

Figure 2.9 A proposed market mechanism for utilizing the flexibility for central and local ancillary services.

3 Definition of flexibility steering signals

3.1 Official approaches

3.1.1 OpenADR

OpenADR is an open standard for communication of DR and Distributed Energy Resources (DER) signals from providers or Virtual Top Nodes (VTN) to customers or Virtual End Nodes (VENs) using a common language [58]. This standard is based on Energy Interoperation v1.0 (EI) from OASIS (Organization for the Advancement of Structured Information Standards) [59].

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A diagram of the different types of nodes and the information paths between them is shown in **¡Error! No se encuentra el origen de la referencia.**. In this diagram, it can be seen that a VTN can communicate to one of more VENs. Furthermore, there can be intermediate nodes that act as VEN and VTN (Aggregated Loads).

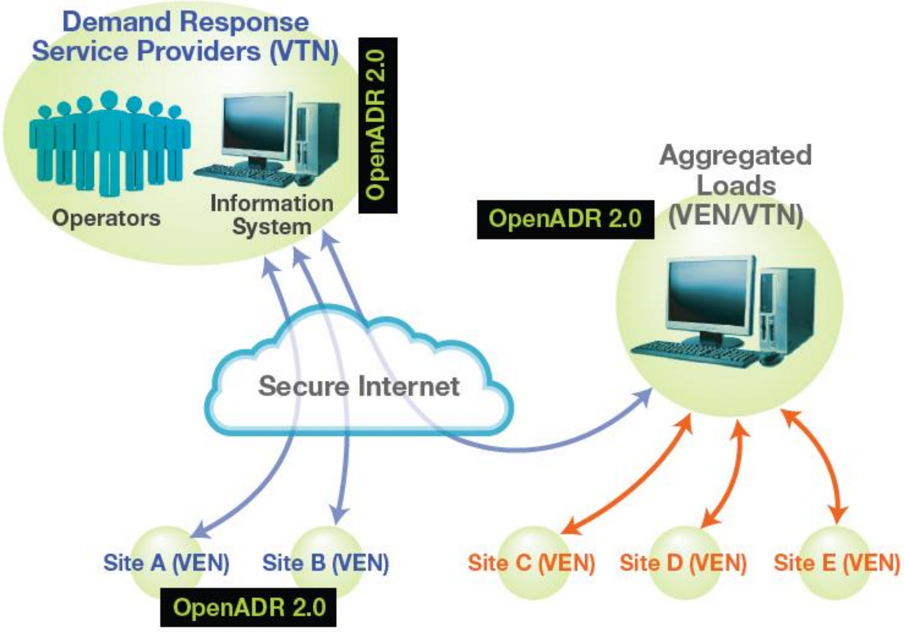

Figure 3.1: OpenADR diagram [58]

This standard can help to increase the integration of DER into the grid by lowering costs, assuring interoperability, increasing the reliability and enhancing the flexibility [60]. However, the implementation of OpenADR is not straightforward and its characteristics, such as event signals or report formats, must be adapted for the different DR programs [61]. For this, the "OpenADR 2.0 Demand Response Program Implementation Guide" [61] includes a list of event signals (shown in **¡Error! No se encuentra el origen de la referencia.**) and specific templates for each of the following DR programs:

- Critical Peak Pricing
- Capacity Bidding Program
- Thermostat Program/Direct Load Control
- Fast DR Dispatch/Ancillary Services Program
- Electric Vehicle (EV) DR Program
- DER DR Program

Table 1: OpenADR signals (OpenADR Alliance, 2016)

Signal Name	Signal meaning
BID_ENERGY	Amount of energy from a resource that was bid into a program
BID_LOAD	Amount of load that was bid by a resource into a program
BID_PRICE	Price that was bid by the resource
CHARGE_STATE	State of energy storage resource
DEMAND_CHARGE	Demand charge
ELECTRICITY_PRICE	Cost of electricity
ENERGY_PRICE	Cost of energy

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Signal Name	Signal meaning
LOAD_CONTROL	Set load output to relative values
LOAD_DISPATCH	This is used to dispatch load
simple	Depreciated - for backwards compatibility with A profile
SIMPLE	Simple levels (OpenADR 2.0a compliant)

[62] stated that even though the Open ADR protocol is very “general” it can be applied to many different DR programs and many different architectures, which offers a significant range of possibilities. This is highlighted in the implementation guide elaborated by the Sacramento Municipal Utility District (SMUD), where they included nine different use cases [63]. Furthermore, this standard has been implemented in several EU projects such as Orchestrating Smart Charging in mass Deployment [64], Holisder [65], FLEXcoop [66] and DELTA [67].

Regarding the flexibility calculation, in their study, [62] investigated a DR solution based on the OpenADR standard. According to their approach, the flexibility offers were calculated as follows:

- **Power estimation**: at the start of the day, the Building Management System (BMS) estimates the power consumption and generation (if any). This results in the maximum and minimum values for each of the hours of the day.
- **Baseline calculation**: the baseline is calculated using the mean of consumptions of previous days for each hour.
- **Flexibility calculation**: the flexibility is calculated as the baseline minus maximum expected consumption.

3.1.2 USEF

The Universal Smart Energy Framework (USEF) was founded by seven companies (ABB, Alliander, DNV, Essent, IBM, ICT Group and Stedin) with the purpose of providing the market structure, rules and tools to support adequate energy flexibility trading with benefits to all stakeholders [6]. The main benefits of the USEF are [6]:

- **It supports** the implementation of **the** EC’s directive on electricity market design with respect to demand-side participation.
- **It supports** smart energy transition **through** innovation, integration and scaling.
- **It** reduces the cost to connect different technologies and projects to the energy system **through standardization.**

The time granularity used for forecasts, flexibility offers, etc. agrees with the imbalance settlement period (ISP) which is 15 minutes in most European countries. Flexibility is defined as the deviation between the actual power consumption/generation and the estimated power or baseline. The USEF originally assumed that the baseline is a forecast provided by the Aggregator, which is known as nomination or D-prognosis. However, other baselines based on a measurement (MBMA-method), or a mathematical formula can be also used. The flexibility is expressed in power (W) while the activation is typically expressed in energy (kWh) [6], [68].

The framework defines different roles and flexibility services for both implicit flexibility and explicit flexibility. In addition, different remuneration types are considered.

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3.1.2.1 USEF Roles

The roles defined by the USEF are listed below [6]:

- Active Customer: **consumes, generates and/or stores electricity**
- Aggregator: **accumulates flexibility from several Active Customers**
- Supplier: **supplies energy to its customers**
- Balance Responsible Party **(BRP)**: **is contracted by the supplier and it is responsible for the imbalances in the electricity system.**
- Distribution System Operator (DSO): **operates and maintains the distribution system in a certain area, ensuring the long-term ability of the system.**
- Transmission System Operator (TSO): **transports energy in a certain area keeping the system in balance.**
- Producer**: feeds energy into the grid.**
- Energy Service Company (ESCo)**: offers energy-related services to Active Customers.**
- Trader**: buys and re-sells energy in the market**
- Exchange**: provides brokering between electricity Traders, Suppliers, BRPs and Aggregators.**
- Common Reference Operator **(CRO): is responsible for the information regarding connections and congestion points in the network.**
- Metered Data Responsible **(MDR): validates measured data.**
- Imbalance Settlement Responsible **(ISR): establishes and communicates the realized consumption and production volumes per ISP.**
- Balancing Service Provider **(BSP): provides balancing services to TSOs.**
- Congestion Management Service Provider **(CMSP): provides constraint management to a DSO or the TSO.**
- Capacity Service Provider **(CSP): provides adequacy services to either the TSO or a BRP.**

3.1.2.2 USEF Flexibility Services

3.1.2.2.1 Implicit Flexibility

The flexibility is considered implicit when the Active Customers adapt their consumption/generation based on variable tariffs. The USEF defines four different implicit flexibility services [6]:

1. Time-of-use (ToU) optimization based on load shifting from high to low-price intervals.
2. In-home self-balancing **based on the** difference in the prices for supply from the grid and feed-in to the grid**.**
3. kWmax control based on reducing the maximum load (peak shaving) within a predefined period**.**
4. Emergency power supply for islanding during grid outages**.**

3.1.2.2.2 Explicit Flexibility

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The flexibility is considered explicit when the Active Customers adapt their consumption/generation based on requests from the DSO/TSO via the Aggregator. The USEF defines four different groups of explicit flexibility services [6]:

1. **Wholesale services**: including Day-Ahead Intraday and generation optimization and self-balancing services.
2. **Constraint management**: including voltage control, grid capacity and congestion management and controlled islanding and restoration.
3. **Balancing**: to restore system frequency to its nominal frequency of 50 Hz. Balancing services include Frequency Containment Reserve (FCR), Automatic Frequency Restoration Reserve (aFRR), Manual Frequency Restoration Reserve (mFRR) and Replacement Reserve (RR).
4. **Adequacy**: to increase security of supply in the long-term. Adequacy services include capacity markets, capacity payments, strategic reserves and hedging.

3.1.2.3 USEF Flexibility Remuneration

The USEF considers two types of flexibility remuneration:

- **Availability remuneration**: the Aggregator receives a fixed price for availability of capacity but can also suffer from penalties if the delivery requirements are not met.
- **Activation remuneration**: based on the requested or activated volume of energy (kWh) or power (kW). The calculation of the activated volume depends on the baseline calculation methodology chosen.

3.2 ebalance-plus proposition

The ebalance-plus consortium has considered a priority the definition of a consistent flexibility measurement. The IEA defines the energy flexibility as “the extent to which a power system can modify electricity production or consumption in response to expected variability or otherwise”. According to this definition, the flexibility is dynamic or, in other words, it is time dependent and any interaction with a system trying to modify its behaviour, flexibility changes. Therefore, the energy flexibility cannot be considered a commodity as it is, what makes the market acceptance difficult for two main reasons:

(1) Estimation accuracy. In general, any energy system can be composed of consumption loads, generation and storage units, whose flexibility can be estimated with prediction models separately. The flexibility, both power and energy at any time is the aggregation of the variation extent of generation and consumption predictions and the charging/discharging operation scheduled by the storage units.

$$P_{flex} = \Delta P_{cons} + \Delta P_{gen} + \Delta P_{storage}\ (Power\ flexibility)$$
$$E_{flex} = \Delta E_{cons} + \Delta E_{gen} + \Delta E_{storage}\ (Energy\ flexibility)$$

The ΔP_{cons} (increment of power consumption) is only possible if energy loads can be interrupted or shifted, ΔP_{gen} (increment of energy generation) is only possible when generation system (especially power inverters) can cut the rated power (as known as power curtailment) and $\Delta P_{storage}$ (increment of power) is in general possible if storage system are controllable and manufacturer’s constraints are respected (e.g., number of charging cycles per day).

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At first, the estimation of the energy flexibility can be considered a matter of the accuracy of prediction algorithms for consumption and generation units and optimization algorithms regarding storage units. The case of energy storage is the simplest, as these systems are programmed and optimised on the basis of technical and economical requirements. On the other hand, in the case of generation systems, their estimation is also possible if the prediction models (e.g., weather predictions in case of renewable sources) and systems are adjusted accordingly. The main drawback is the **building energy consumption**, especially regarding HVAC and domestic hot water (DHW), which represent the highest term in energy bills.

The HVAC consumption depends mainly on the building occupancy, outdoor conditions, performance operation of equipment and the building components (geometry, materials, workmanship, among others) that characterize the **building thermal inertia**. This means that if some arbitrary interruption of the HVAC operation happens to modify power or energy consumption, building occupants can become into discomfort levels. On the other hand, the energy supply to keep building comfort thresholds may be assumed as constant over a day, thus the energy saved in some period must be consumed afterwards to keep comfort conditions (with higher or lower costs). Therefore, to exploit the energy flexibility of HVAC systems, it is necessary two conditions:

- Enough building thermal inertia (i.e., slowly evolution of indoor temperature) to provide a significant energy or power flexibility without compromising comfort levels.
- Models and algorithms predicting accurately the indoor conditions anytime under some operation change.

First, building HVAC must have enough capacity to balance the potential temperature deviations over the day. For example, it is necessary more energy to reduce the indoor temperature 1º C if the outdoor temperature is 40º C instead of 25º C, or if solar radiation is the main energy flow or if indoor conditions (e.g., occupancy) increase the temperature naturally. Therefore, the energy flexibility depends on the HVAC rated capacity and outdoors conditions. This property must be considered in thermal modelling, otherwise, the energy flexibility may be overestimated and cause discomfort.

On the other hand, although modelling accurate prediction algorithms of building thermal inertia is possible, it requires several types of reliable sensors that provide all the parameters involved and robust physical or AI-based models that requires long simulation or training time respectively. Therefore, research on hybrid modelling as proposed and developed in ebalance-plus (grey-box models) allows reducing training time and the need of deep monitoring.

(2) Dynamic principle. As explained above, robust prediction models estimating actual flexibility is essential to establish fair market operations and energy management solutions to end customers, guaranteeing that more flexibility means more benefits. Considering that the accuracy of flexibility is enough to participate in balancing market operations as expected, the dynamic principle remains and from the moment that the flexibility is activated (i.e., the assets increase or reduce the expected energy consumption), predictions become outdated. This basic principle requires that flexibility mechanisms must estimate and manage the energy flexibility for all the

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scenarios, (i.e., power, duration, and time), what makes management approaches unaffordable with usual prediction algorithms.

The proposition

These two reasons presented have been considered to create a reliable flexibility management ecosystem based on the principle that the energy flexibility must be a commodity, i.e., the measurement and verification procedure must be common for all the technologies and useful for all the stakeholders. The goal is to create a trust environment where energy retailers, aggregators, prosumers and network operators can exchange the flexibility in the same terms as the electric energy or power.

Assuming that energy flexibility must be a commodity, the first step was to adopt the most usual timeframe at European level by the market, i.e., **15-minute energy monitoring**. This time interval is considered as the minimum time that the customer or DER can provide flexibility to the system. Therefore, the customer offering flexibility can do it in multiples of 15 minutes, starting from the first time of the local day-ahead market. In case of France, the time interval considered is 30 minutes. The main benefit of this approach is that the aggregation of flexibility is the sum of individual flexibility of devices, customers, district, etc.

Using the previous assumption, the number of scenarios is reduced significantly and can be calculated with a **what-if analysis** approach. The what-if analysis aim at calculating the maximum flexibility (power and duration) available for every 15 minutes in period of 15 minutes, over 24 or 48 hours depending on the time horizon needed. The main benefit is that the maximum number of optimization problems or forecasts is 96 operations in 24 hours, totally suitable for most of IoT hardware in the market.

Finally, it is proposed the data format in. json. For simplicity, the period is expressed as integer instead of local time. The data exchange format includes: user id, timestamp (calculation time), power/energy forecasting, positive flexibility (flex.up), negative flexibility (flex.down), cost (flex.cost) and the parameter “partial” means if the flexibility power can be partially (“on”) released or must be released totally in time (“off”).


```
“user.id”: “number.id”,
“timestamp”: "0000000000",
{
“period”: k,
“power.forecasting”: 100,
“energy.forecasting”: 25,
“flex.up”: {
“power”: [Fk, Fk+1, Fk+2, ⋯, FM],
“flex.cost”: 0.10,
“partial”: “on”,
},
“flex.down”: {
“power”: [Fk, Fk+1, Fk+2, ⋯, FM],
“flex.cost”: 0.20,
“partial”: “off”,
},
}
}
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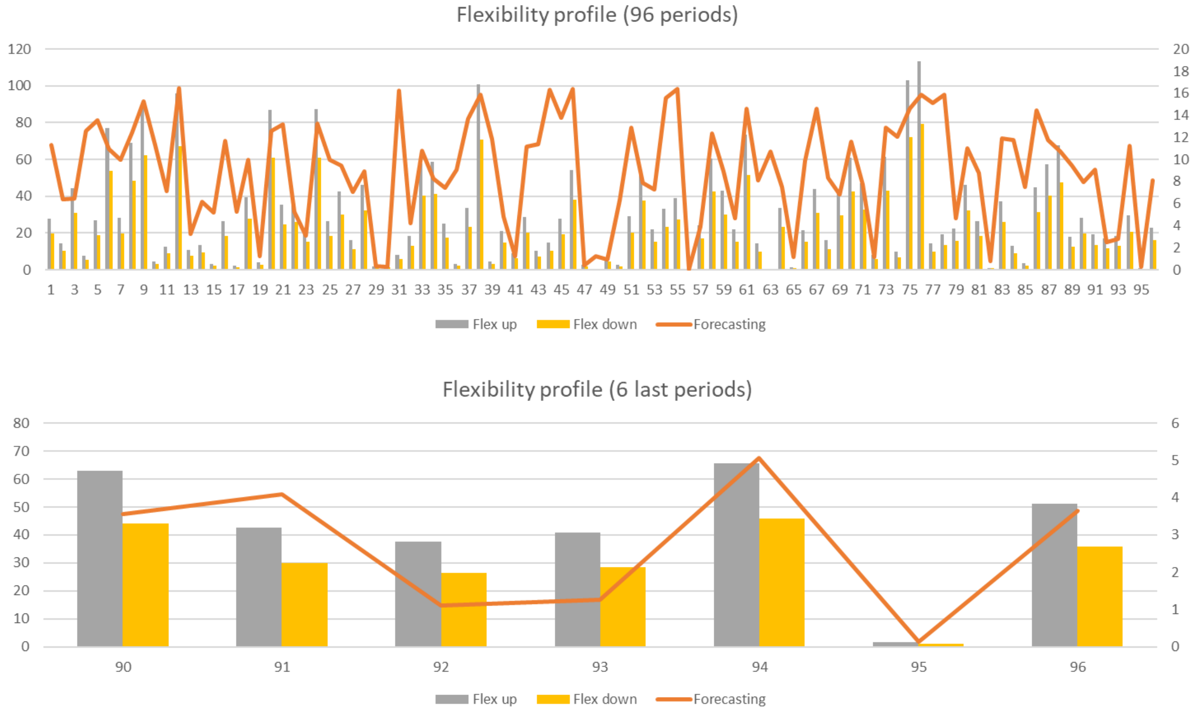

Figure 3.2 Graphical representation of energy flexibility

Finally, other proposition presented is the "flexibility cost". Flexibility cost is the difference between the optimal scenario and the cost that the customer/DER offers for activating the flexibility in a specific time. In other words, the minimum price that must negotiate to keep at the minimum energy cost. The definition is presented as follows:

- Number of periods: $k = 1, \dots, M$. In case of quarter-hour energy profiles $M = 96$
- Energy cost (€) by period k: $e_{cost}[k]$
- Optimal energy profile from period m: $E_c[k], k \geq m$
- Updated energy profile after flexibility request in period m: $E_c^*[k \geq m]$
- Flexibility cost (€/kWh) in period m: $flex_{cost}[m]$
- Flexibility request (kWh) in period m: $flex_{request}[m]$

$$flex_{cost}[m] = \frac{\sum_{k \geq m} e_{cost}[k](E_c^*[k] - E_c[k])}{flex_{request}[m]}, m = 1, \dots, M$$

4 Flexibility scenarios in ebalance-plus

The ebalance-plus project has defined three high-level use cases that must cover the most interesting flexibility services in the future focused especially on end customers (buildings, EV users, facility managers and DER managers).

- Flexibility services I: DER flexibility management
- Flexibility services II: VPP services for buildings

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- Flexibility services III: Cost/CO2 optimization

These scenarios are described in the following sections.

4.1 Flexibility services I

Flexibility services I (project use case number 8) describes the management of distribution energy resources in the context of flexibility management. A new figure named DER manager is the actor providing a district facility composed of electric vehicle charging points supplied by PV energy in combination with BESS and integrated in the grid with high-efficient power electronics. The DER manager provides charging services while participates in balancing (ancillary) services and local flexibility markets together with energy aggregators and the DSO. The whole solution can be considered a virtual power plan (VPP) model at district level. In this case, ebalance-plus proposes a micro-DC network to take advantage of higher conversion and transmission efficiency, lower cost of energy converters and convenient controllability with less complexities (harmonics, synchronization, reactive power control, frequency…) than AC networks.

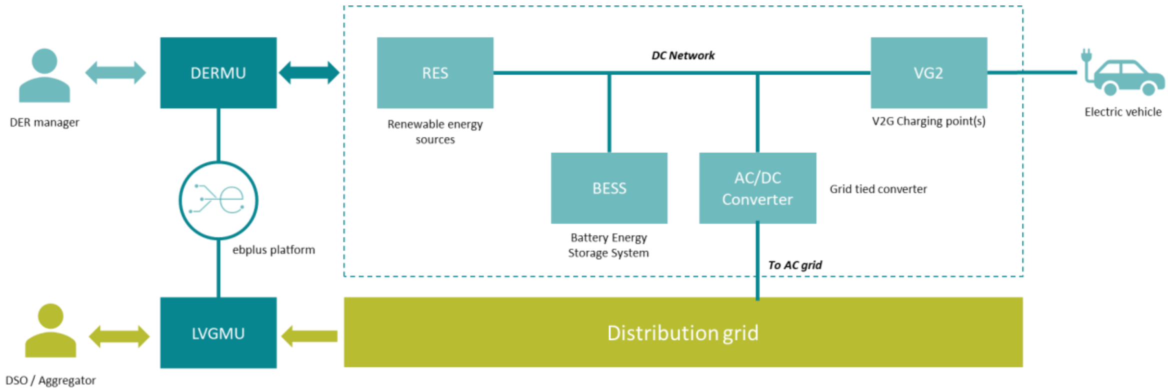

Figure 4.1 ebalance-plus architecture controlling DER facility for flexibility management

This scenario requires a two-level control: resource management in a DC micro-network algorithm and the flexibility management.

4.1.1 Resource management in a DC micro-network algorithm

For the management of resources and in particular of energy from renewable sources in a DC network, different solutions can be used. First of all, it is necessary to consider what is the objective function, what are the resources to be managed and the electric setup of the microgrid. Two main management strategies are introduced: centralized and DC bus Signalling (DBS):

- The first management mode, that is centralized, involves the implementation of an algorithm which, depending on the inputs and resources present, can use different objective functions, which can be the minimization of the the maximum power exchanged with the grid, minimization of energy exchanged with the grid, maximization of resources and other similar targets.
- The second way of managing resources is DBS. It works based on the DC-bus voltage, i.e., the bus on which the energy resources are interfaced. Thanks to this management mode, a communication platform is not needed, but they can work according to a common goal by measuring the voltage of the DC-bus.

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Both control algorithms are described as follows:

Centralised algorithm

The centralized model can be divided into two steps: the first that operates the day ahead and the second, that is a running an optimization, which operates almost in real-time; a schematic view of the algorithm is reported in Figure 4.2.

To run the first part of the algorithm, there are three different types of inputs:

- A series of inputs that do not depend on users: day-ahead production and load forecasts, the state of charge of the different storage systems, any requests from grid operators, and other similar data.
- Inputs that are dependent on users like habits, scheduling, any arrival, and departure times in case of electric vehicles, target temperatures of air conditioning systems, and other similar variables.
- Others depending on rated specifications of energy resources connected like rated powers of the converters, storage systems capacity, any limits on the state of charge, the type of storage systems, as well as the type and number of present resources.

These variables are the inputs of a day-ahead optimization model, whose objective function depends on the power exchanged with the grid, implementing any function related on it. Among the several inputs to the model there is also the possibility of considering the availability of flexibility, in order to be able to carry out some flexibility operations next day; this input is optional and depends on the objective function of the model.

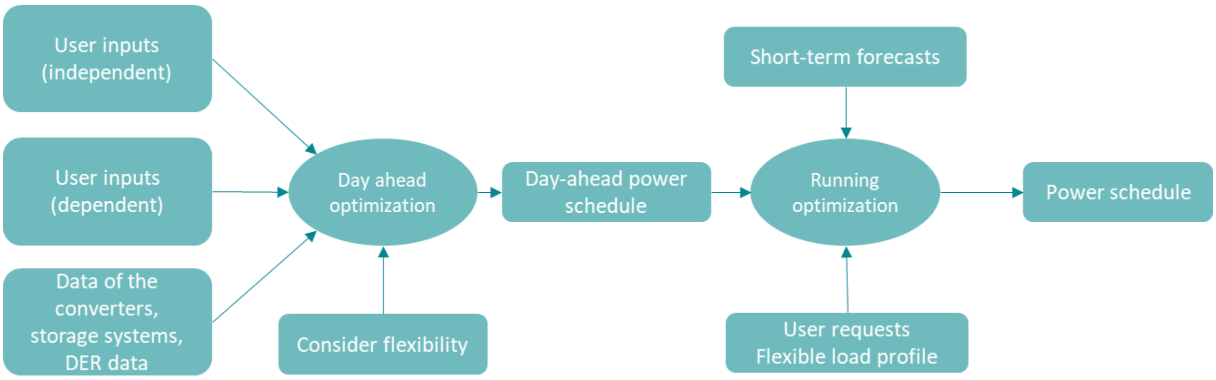

Figure 4.2 DC network centralized algorithm scheme

At the end of this first step, the power profiles that should be exchanged with the grid and with the storage systems are obtained: these profiles are dependent one each other, so that only the exchange profile with the grid could be used to determine the others. These power profiles are used to run optimization algorithms and calculate the energy exchange with short-term forecasts after a flexibility request.

DC Bus Signalling (DBS) algorithm

The microgrid management algorithm through DC bus signalling (DBS) technology considers the microgrid power converters connected to the same DC-bus. They are

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not commanded by any external algorithm, rather they modify their operating mode, therefore the power to be exchanged, by measuring the voltage on the DC-bus.

In fact, according to the available resources, different thresholds which indicate the different operating modes are established. These thresholds depend on the renewable generation, the presence of storage systems, and the connection with the grid. Voltage levels in which different operations take place are then defined, when the storage systems supply or absorb power, when the injection or adsorption from the grid is enabled, when the renewable production plants can work at maximum power and when instead it is necessary to cut the same power.

The different thresholds, as shown in Figure 4.3, are defined by two voltage levels. In each threshold various resources are suitably controlled, according to a predetermined objective, by modifying the setpoints of the converters. According to this objective, the control methods can also be modified between the different thresholds. For example, the control of a converter in the same threshold can be different if the main objective is to maximize the use of renewable resources or ensure the continuous supply of electricity.

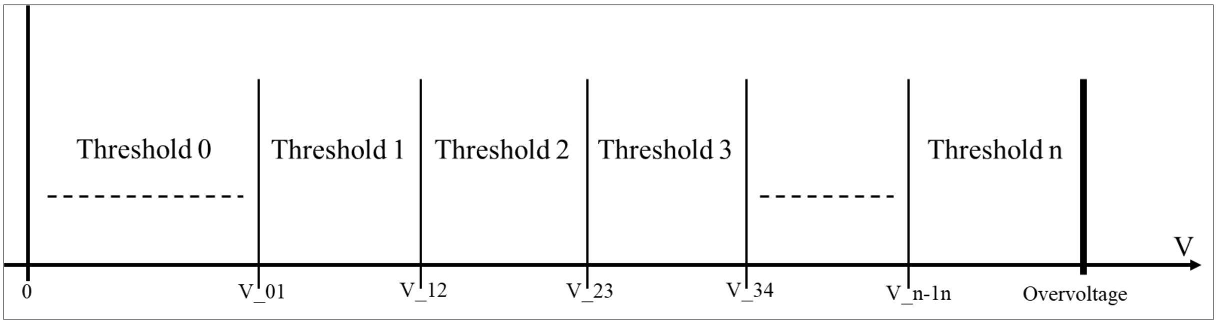

Figure 4.3 A threshold scheme of the DBS algorithm

In case of several microgrids interfacing on the same DC-bus, managing similar resources, it is necessary to define "intervention coefficients" for the different microgrids, in order to correctly distribute the power flows. The same event can happen in the same microgrid, or in several microgrids interfaced with each other, if several storage systems are present or even different types of them. In this case their contribution will also be splitted according to appropriate coefficients.

This operating mode is independent of any type of communication between the different converters, thus allowing it to operate even without external communications, autonomously for the objective set a priori.

Interaction of the two strategies (under discussion)

The two management strategies presented can be combined. In particular, considering the centralized algorithm previously described, whose output are power profiles that are sent to the different microgrids. In this case, the goal of these microgrids is to follow such profile but using the DBS at the basic operation of the microgrid for their devices. At the same time, the DBS represents a buffer strategy to use if there is no communication of the microgrids with other external components, thus managing to pursue the set goal.

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In the ebalance-plus context, this use case is setup in the existing microgrid of the University of Calabria and demonstrated in the University of Málaga. To increase the robustness of the solution presented and facilitate the deployment and integration of solutions, the DC/DC power inverters involved (PV, BESS and V2G charging points) will operate under a DBS approach but punctually commanded by the ebalance-plus platform flexibility or resilience mechanisms. In this way, the voltage of the DC bus will operate under security conditions anytime and even flexibility requests can be refused if some over- or under- voltage conditions can happen.

4.2 Flexibility services II: VPP services for buildings

Flexibility services II aims at describing an innovative mechanism to transform buildings into virtual power plants (VPP) and aggregate multiple users (mainly buildings and facilities) and manage the available energy flexibility to support grid operation (DSO) or aggregator business (local flexibility markets). This mechanism is based on the flexibility definition proposed by ebalance-plus consortium as evolution of the previous FP7 project e-balance, which requires three steps to be implemented:

1. Estimation of flexibility using forecasting models (BESS, HVAC, weather forecasting, PV generation, etc.): generation and update of scenarios every 15 minutes.
2. Optimization of energy assets according to market prices or environmental impact (CO2 reduction) when energy flexibility is not required.
3. Flexibility activation under external steering signals due to grid congestion (DSO) or market opportunities (aggregator).

The main point and difference regarding existing approaches is that, during the first step, the estimation of flexibility is declared to the market (e.g., aggregator) as well as the energy consumption is accounted for billing in case of energy suppliers, following the same organisational structure that could be integrated into smart meters in the future. The flexibility portfolio is update in turn every 15 minutes; thus, the whole system is aware of the total available flexibility with a better accuracy. These benefits are expected to be tested during the project demonstration phase in different configurations and locations (Spain, Italy, France).

Flexibility estimation

The flexibility estimation depends on the physical models or control strategy considered to manage the building assets. This section proposes two generic examples (BESS and HVAC) of how they should be defined and carried out for different assets.

Battery flexibility: $(\mathrm{P}_{flex}^{\mathrm{down}}, t_{down}, \mathrm{P}_{flex}^{\mathrm{up}}, t_{up})$

$$\mathrm{P}_{flex}^{\mathrm{down}}[\mathrm{k}] = \overline{P_{BESS}^{down}} - P_{BESS}^{down}[k] \quad (1)$$

$$t_{down} = \frac{E_c^{BESS}[k] - E_{min}^{BESS}}{P_{flex}^{down}[k]} \quad (2)$$

$$\mathrm{P}_{flex}^{\mathrm{up}}[\mathrm{k}] = \overline{P_{BESS}^{up}} - P_{BESS}^{up}[k] \quad (3)$$

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$$t_{up} = \frac{E_{max}^{BESS} - E_c^{BESS}[k]}{P_{flex}^{up}[k]} \quad (4)$$

Where:

- $E_c^{BESS}[k]$: Energy consumed by the BESS (negative values mean discharging in kWh)
- P_{BESS}^{up}, P_{BESS}^{down}: Max/min power charge/discharge values (input)
- P_{flex}^{down}, P_{flex}^{up}: Estimated power flexibility discharging/charging (kW)
- t_{down}, t_{up}: Estimated flexibility time discharging/charging (s)

HVAC flexibility

Remark: this estimation requires solving an optimization problem every time step and using thermal modelling represented by the beta function.

Heating ($P_{flex}^{heat}, t_{heat}$)

$$\begin{aligned}
&Max\ t_{heat} \cdot P_{heat} \\
&ST && (1) \\
&\beta_{heat}(P_{heat}, t_{heat}) \leq T_{max} && (2) \\
&\overline{P_{HVAC}^{heat}} \geq P_{heat} \geq P_{HVAC}^{heat}[k] && (3) \\
&t_{heat} \geq \tau && (4) \\
&P_{flex}^{heat} = P_{heat} - P_{HVAC}^{heat}[k] && (5)
\end{aligned}$$

Cooling ($P_{flex}^{cool}, t_{cool}$)

$$\begin{aligned}
&Max\ t_{cool} \cdot P_{cool} \\
&ST && (1) \\
&\beta_{cool}(P_{cool}, t_{cool}) \geq T_{min} && (2) \\
&\overline{P_{HVAC}^{cool}} \geq P_{cool} \geq P_{HVAC}^{cool}[k] && (3) \\
&t_{cool} \geq \tau && (4) \\
&P_{flex}^{cool} = P_{cool} - P_{HVAC}^{cool}[k] && (5)
\end{aligned}$$

Where:

- τ : Time step (15 minutes)
- $\beta_{Cool}(P_{cool}, \theta), \beta_{heat}(P_{heat}, \theta)$: Temperature evolution functions (º C)
- P_{HVAC}^{Heat}, P_{HVAC}^{Cool}: Heating and cooling power (kW)
- $P_{flex}^{heat}, t_{heat}$: Power heating flexibility (kW) and time (s)
- $P_{flex}^{cool}, t_{cool}$: Power cooling flexibility (kW) and time (s)
- $\overline{P_{HVAC}^{heat}}$, $\overline{P_{HVAC}^{cool}}$: Maximum heating/cooling power (kW)
- $P_{HVAC}^{heat}[k]$, $P_{HVAC}^{cool}[k]$: Estimated/predicted heating/cooling power every 15 minutes (k) (kW)
- T_{min}, T_{max}: Comfort thersholds temperatures (e.g., 21-26º C)

Optimization of energy assets

There are multiple ways to perform optimization problems, both classical approaches using commercial solvers like CPLEX (IBM®) or artificial intelligence algorithms like neural networks, greedy algorithms, genetic algorithms, among others. In the

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ebalance-plus project these approaches are applied and compared in different contexts to evaluate the performance (i.e., time and accuracy). This section proposes a general formulation of an optimization problem (cost and CO2 based) for a building with BESS and HVAC offering flexibility.

$$Min\ \omega_{CO_2} \sum_{k\le K} C_{O2}[k]\cdot(E_{cf}[k]-E_g^{PV}[k]) + \omega_{ener} \sum_{k\le K} e_{cost}[k]\cdot(E_{cf}[k]-E_g^{PV}[k])$$
$$ST$$

"Total energy consumption of building flexible loads (BESS, HVAC)"

$$E_{cf}[k] = E_c^{BESS}[k] + E_c^{HVAC}[k], \forall k$$
$$F_{CO_2} = 1 - F_{ener}$$
$$F_{CO_2}, F_{ener} \in [0,1]$$
$$E_c^{HVAC}[k], E_g^{PV}[k] \ge 0$$

"BESS restrictions"

$$E_c^{BESS}[k] = \tau \cdot \left[\mu_{BESS}[k]\cdot P_{BESS}^{up}[k] - (1-\mu_{BESS}[k])\cdot P_{BESS}^{down}[k]\right], \forall k$$
$$SoC[k] = SoC[k-1] + \frac{E_c^{BESS}[k]}{E_{max}^{BESS}}, \forall k$$
$$P_{BESS}^{up}[k] \le \overline{P_{BESS}^{up}}, \forall k$$
$$P_{BESS}^{down}[k] \le \overline{P_{BESS}^{down}}, \forall k$$
$$SoC_{min}^{BESS} \le SoC[k] \le SoC_{max}^{BESS}, \forall k$$
$\sum_{k\le K}|E_c^{BESS}[k]| \le 2\cdot E_{max}^{BESS}$, *"Battery cycles limitation (2 per day by default)"*
$$\mu_{BESS}[k] \in \{0,1\}, \forall k$$

"HVAC restrictions"

$$E_c^{HVAC}[k] = \tau \cdot \left[\mu_{HVAC}[k]\cdot P_{HVAC}^{Cool}[k] + (1-\mu_{HVAC}[k])\cdot P_{HVAC}^{Heat}[k]\right], \forall k$$
$$T[k] = T[k-1] + \mu_{HVAC}[k]\cdot\beta_{Cool}(P_{HVAC}^{Cool}[k],\tau) + (1-\mu_{HVAC}[k]\cdot\beta_{Heat}(P_{HVAC}^{Heat}[k],\tau), k>1$$
$$T_{min} \le T[k] \le T_{max}, k \in [k_{occupied}, k_{empty}]$$
$$P_{HVAC}^{Heat}[k] \le \overline{P_{HVAC}^{Heat}}, \forall k$$
$$P_{HVAC}^{Cool}[k] \le \overline{P_{HVAC}^{Cool}}, \forall k$$
$$\beta_{Cool}(0,\tau) \equiv \beta_{NE}(\tau)$$
$$\beta_{Heat}(0,\tau) = 0$$
$$T[1] = T_0$$
$$\mu_{HVAC}[k] \in \{0,1\}, \forall k$$

Where:

- $\omega_{CO_2}, \omega_{ener}$: Multicriteria optimization factors (input)
- E_g^{PV}: PV generation forecasting (input in kWh)
- τ : Time step (15 minutes)
- $E_c^{BESS}[k]$: Energy consumed by the BESS (negative values mean discharging in kWh)
- $SoC[k]$: State of charge (%)
- $\mu_{BESS}[k]$, $\mu_{HVAC}[k]$: Binary variables (charge/discharge or heat/cool mode)
- $SoC_{max}^{BESS}, SoC_{min}^{BESS}$: Max/min SoC values (input)
- $P_{BESS}^{up}, P_{BESS}^{down}$: Max/min power charge/discharge values (input)
- $E_c^{HVAC}[k]$: Energy consumed by the HVAC
- $T[k]$: Indoor temperature (º C)
- $\beta_{Cool}(P_{cool},\theta), \beta_{heat}(P_{heat},\theta)$: Temperature evolution equations (º C)
- $\beta_{NE}(\tau)$: Natural temperature evolution (without HVAC system)
- $P_{HVAC}^{Heat}, P_{HVAC}^{Cool}$: Heating and cooling power (kW)

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Flexibility management algorithm

Figure 4.6 shows the flexibility management algorithm using BPMN 2.0. The algorithm is split into two scenarios: normal (without flexibility requests) and flexibility activation. Every 15 minutes the CMU or DERMU will collect data from sensors and forecasting services, perform the flexibility estimation and broadcast the flexibility profile to the upper level, in this case the LVGMU, which aggregates the whole flexibility profile downwards. The energy aggregator can access the flexibility profile of their customers and this flexibility is available at grid level to support grid congestion. In this way, both local flexibility markets for grid congestion and general market operations are addressed. The second part of the algorithm represent the activation of energy flexibility. The request can be done on demand from the energy aggregator or in case of some grid congestion at LVGMU or MVGMU level. As the energy flexibility profile has been declared previously, every unit receives the flexibility request and activate the amount of flexibility requested by its LVGMU. After that, the process continuous as the normal operation, estimating and updating the flexibility profile.

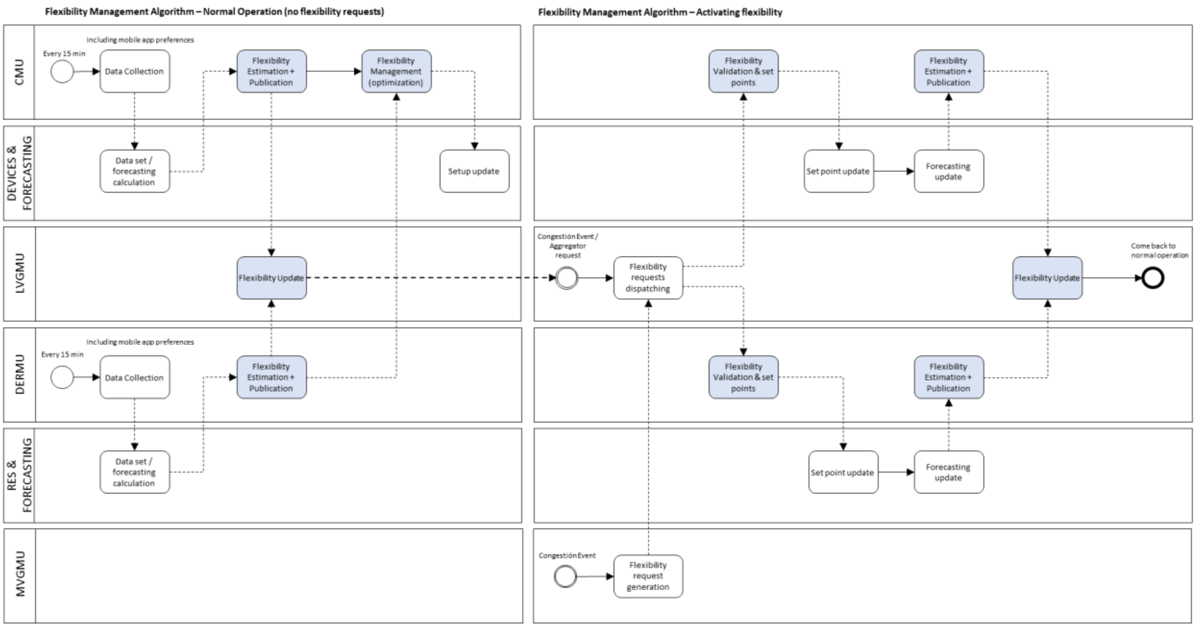

Figure 4.4 Flexibility management in the ebalance-plus platform

4.3 Flexibility services III: Cost/CO2 optimization

As described in Deliverable 6.1 [69], the objective of use case number 10 (UC10) is to unlock the energy flexibility potential of different Danish summerhouses with indoor swimming pools, and enable their participation in price-based demand-response programs, while maximising comfort and minimising CO2 emission and costs. In this respect, model predictive control (MPC) appears to be the natural framework for design a controller capable of:

- Reducing energy bills and/or CO2;
- Enabling automatic load-response to price signals (i.e. price-based demand response);
- Increasing energy efficiency (by optimising energy performance).

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As its name suggests, MPC relies on a model of the system to be controlled, which gives the capability to optimise the control action, while keeping the system dynamics and impact of future disturbances into account. This is achieved by solving at each control time step ***t*** an open-loop optimal control problem, whose aim is to minimise a given objective function ***J*** (e.g. total cost or CO2 emissions) over a finite prediction horizon ***τ***. Once the OCP is solved, the controller implements the optimal control action over the control horizon only and the system moves to the next control time step where the whole process is repeated in a rolling-horizon fashion. In this way, an MPC has the capability to anticipate future events (e.g. energy prices, weather conditions, or grid requests) and adjust the control action accordingly (PID controllers do not have this predictive capability). This capability to adapt autonomously to a changing environment (e.g. stochastic disturbances) is crucial to unlock energy flexibility and minimise energy-related emissions. Moreover, this iterative optimisation process also allows the possibility to introduce feedback in the evaluation of the control action. MPC has been successfully applied to several applications in the energy and buildings field, such as indoor temperature control and optimal control of thermal/electric storages and renewables generation [70].

End users equipped with price/CO2 responsive controllers could benefit from cost and energy savings, and, at the same time, grid operators could exploit the unlocked flexibility to operate the grid more efficiently and to postpone capital-intensive grid upgrades. As a result, the whole society can benefit from renewable integrations, and hence from a cleaner and sustainable energy supply.

Model development for control purposes

Figure 4.5 shows a schematic of the heating system that supply hot water to the swimming pool together with the sensors and digital technologies (e.g., Control Management Unit / Gateway) with which the ebalance-plus platform interact with. A detailed description of the UC10 pilot site can be found in Deliverable 6.1.

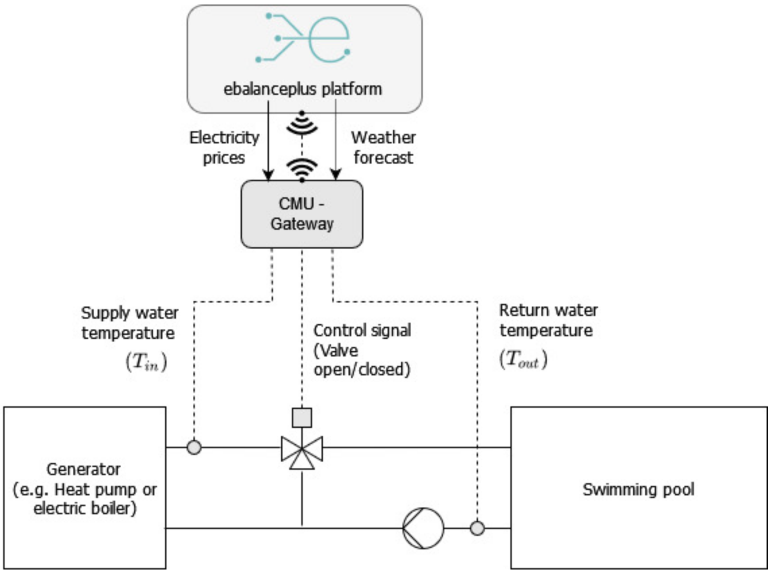

Figure 4.5 Schematic of the swimming pool heating system together with the ebalance-plus experimental set up.

Readings from supply and return temperature sensors, together with weather data retrieved from the ebalance-plus platform are used to build the model of the plant used

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by the MPC controller for prediction calculation. By denoting with T_{in} and T_{out} the supply and return water temperature, respectively, with the latter assumed equal to the pool bulk temperature, a possible formulation of the differential equations governing the system dynamic could be:

$$C_{in}\,\dot{T}_{in} = \dot{m} \cdot c \cdot \ (T_{out} - T_{in}) + \ P_{el} \cdot \eta_{gen} \cdot \delta_V \tag{1a}$$
$$C_{out}\,\dot{T}_{out} = \dot{m} \cdot c \cdot \ (T_{in} - T_{out}) + UA \cdot (T_{env} - T_{out}) \tag{1b}$$

Where C_{in} and C_{out} are the thermal capacities of the water content within the generator and the swimming pool, respectively; $\dot{m}$ is the mass-flow rate of the water circulated by the pump; UA is the thermal conductance of the swimming pool envelope; T_{env} is the temperature of the environment surrounding the swimming pool envelope (e.g. ground temperature); P_{el} and η_{gen} are the generator power input and efficiency, respectively. δ_V is a binary variable that is equal to one when heat is provided to the pool (valve open), and zero when no heat is provided (valve closed), while Δt is the length of the control time step.

Given the system of differential equations (Eq.1) it is then possible to derive the discrete-time state space model which will be used for control purpose, by using of a zero-order-hold sampling of the input signal:

$$\begin{bmatrix} T_{in}^{t+1} \\ T_{out}^{t+1} \end{bmatrix} = \begin{bmatrix} 1 - \frac{\dot{m} \cdot c \cdot \Delta t}{C_{in}} & \frac{\dot{m} \cdot c \cdot \Delta t}{C_{in}} \\ \frac{\dot{m} \cdot c \cdot \Delta t}{C_{out}} & 1 - \frac{\dot{m} \cdot c \cdot \Delta t}{C_{out}} - \frac{UA \cdot \Delta t}{C_{out}} \end{bmatrix} \cdot \begin{bmatrix} T_{in}^{t} \\ T_{out}^{t} \end{bmatrix} + \begin{bmatrix} \frac{\eta_{gen} \cdot P_{el}^{t} \cdot \Delta t}{C_{in}} \\ 0 \end{bmatrix} \cdot \delta_v^t + \begin{bmatrix} 0 \\ \frac{UA \cdot \Delta t}{C_{out}} \end{bmatrix} \cdot T_{env}^{t} \tag{2}$$

Eq. 2 can be stated in a more compact form by using vector notation:

$$\mathbf{T}^{t+1} = \boldsymbol{A} \cdot \boldsymbol{T}^{t} + \boldsymbol{B} \cdot \boldsymbol{u}^{t} + \boldsymbol{D} \cdot \boldsymbol{d}^{t} \tag{3}$$
$$\boldsymbol{y}^{t} = \boldsymbol{C} \cdot \boldsymbol{T}^{t} \tag{4}$$

Where $\boldsymbol{A}$, $\boldsymbol{B}$, $\boldsymbol{C}$ and $\boldsymbol{D}$ are the discrete state-space matrices; $\boldsymbol{T} = [T_{in} \quad T_{out}]^{\boldsymbol{T}}$ is the state vector; $\boldsymbol{y}$ is the measured output vector; $\boldsymbol{u}$ is the vector of control variables (i.e., the valve position) and $\boldsymbol{d}$ is the vector of disturbances (e.g. ground and indoor temperatures, heat gains, etc.).

Optimal control problem formulation

The control objective is to minimise the system operational cost over a prediction horizon N, while satisfying the occupancy comfort requirements.
By denoting the electricity price as c_{el} the objective function J can be formulated as follows:

$$min\, J = \sum_{t=1}^{N} c_{el}^{t} \cdot P_{el}^{t} \cdot \delta_V^t \cdot \Delta t \tag{4}$$

The range within which the pool temperature is allowed to vary gives comfort constraints:

$$T_{out}^{min} \leq T_{out}^{t} \leq T_{out}^{max} \qquad\qquad \forall\, t = 1, \dots, N \tag{5}$$

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Similarly, Eq. 6 bounds the supply water temperature within the range defined by its minimum and maximum values:

$$T_{in}^{min} \leq T_{in}^{t} \leq T_{in}^{max} \qquad \forall\, t = 1, \dots, N \qquad (6)$$

Finally, given the state-state representation of the system dynamic (Eqs. 3-4), the optimal control problem to be solved at each control time step reads as follows:

$$min\, J = \sum_{t=1}^{N} c_{el}^{t} \cdot P_{el}^{t} \cdot \delta_{V}^{t} \cdot \Delta t \qquad (7)$$

$$\text{s.t.} \quad \mathbf{T}^{t+1} = \boldsymbol{A} \cdot \boldsymbol{T}^{t} + \boldsymbol{B} \cdot \boldsymbol{u}^{t} + \boldsymbol{D} \cdot \boldsymbol{d}^{t} \qquad \forall\, t = 1, \dots, N \qquad (8)$$

$$\boldsymbol{y}^{t} = \boldsymbol{C} \cdot \boldsymbol{T}^{t} \qquad \forall\, t = 1, \dots, N \qquad (9)$$

$$T_{out}^{min} \leq T_{out}^{t} \leq T_{out}^{max} \qquad \forall\, t = 1, \dots, N \qquad (10)$$

$$T_{in}^{min} \leq T_{in}^{t} \leq T_{in}^{max} \qquad \forall\, t = 1, \dots, N \qquad (11)$$

$$\delta_{v}^{t} \in \{0,1\} \qquad \forall\, t = 1, \dots, N \qquad (12)$$

It is worth underlining that exposing end users to time-varying prices reflective of the grid and generation costs allows for an increase in end users awareness of their impact on their consumption levels on the system costs. Moreover, it incentivises them to be flexible and shift their consumption from high to low tariff hours, thus relieving the stress on the grid (e.g., resolve grid congestion or reduce demand peaks).

BPMN 2.0 diagram

Figure 4.6 shows the process through which the economic MPC is implemented. At customer premise, the control management unit (CMU), which also works as a gateway, runs in stand-by mode and it is constantly waiting to get new information (i.e., price and weather forecasts) from the ebalance-plus platform. Updated forecasts and electricity prices are retrieved from external data providers through rest APIs. Once the new information is available, the algorithm running on the CMU software solve the optimal control problem over the time horizon to which the price and weather forecast data refer. Finally, the new optimal control settings are sent back to the local controller of the heating system, which updated its status based on the new setting received. The whole procedure is then repeated in a rolling horizon fashion every time that new data are available at CMU level.

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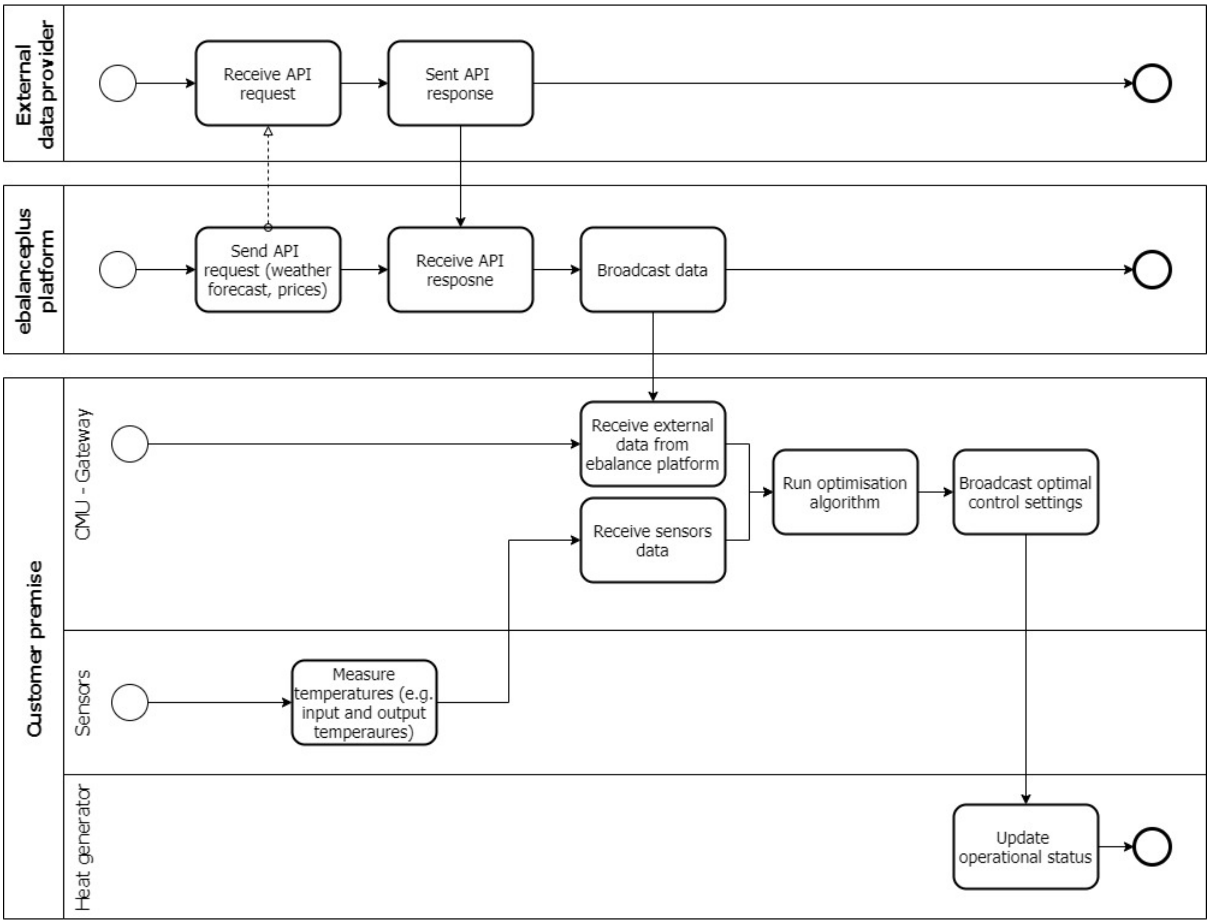

Figure 4.6: BPMN 2.0 diagram of the price-responsive predictive controller.

5 Energy flexibility algorithms

In this chapter, several approaches (hybrid grey-box, fuzzy logic, and deep learning) to estimate the energy flexibility in buildings considering demand, storage and generation sources are presented. These algorithms will be tested in the ebalance-plus demo sites (Spain, Italy, and France), thus, the conclusions obtained may differ from the following descriptions at the end of the project.

5.1 HVAC energy flexibility estimation: grey-box modelling

One of the main sources of consumption and flexibility in buildings is the heating, cooling, ventilation, and air conditioning (HVAC). Buildings' thermal inertia can be exploited as energy storage, while comfort conditions are maintained (21-26º C in general terms). However, the characterization of thermal inertial is complex and depends on static (construction elements) and dynamic (occupancy and user behaviour) parameters and conditions. This section described the physic problem and how it has been addressed in ebalance-plus project with a hybrid grey-box model approach.

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5.1.1 Problem Description

To estimate HVAC energy flexibility, we need to predict the thermal evolution of the building under different operation conditions of the HVAC system. This prediction can be obtained by using a grey-box model [71], which combines a white-box model with a black-box model. White-box models are based on theoretical knowledge about the problem to be solved and black-box models are built on statistical information from the experimental data. More specifically, the white box models a thermal network to solve the heat transfer problem while the black box estimates the parameters of the transfer equations through historical data (temperature, solar radiation, and HVAC system status).

In the grey-box model, the heat flow can be modelled by an electric circuit analogy 1R1C (see Figure 2.1) where heat flow is represented by current, temperatures are represented by voltages, heat sources are represented by constant current sources, absolute thermal resistances are represented by resistors and thermal capacitances by capacitors. The parameters that characterize each of these elements can be estimated using a Linear Regression Model with the historical data available, or any other artificial intelligence model.

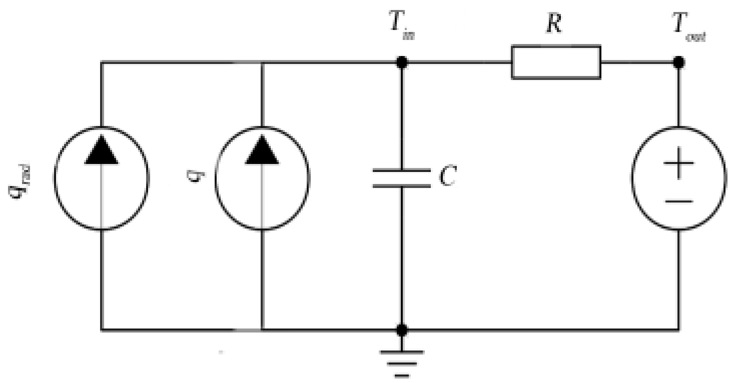

Figure 5.1 Equivalent thermal model (1R1C) used for the model

In our case, the thermal circuit includes:

- T_{in}: Indoor temperature of the building (ºC)
- T_{out}: Outdoor temperature (ºC)
- R: Thermal resistance of the building (m²ºC/W)
- C: Thermal capacity of the building (W/m²ºC)
- q_{rad}: Solar radiation power on the building (W/m²)
- q: HVAC system power consumption (positive value for heating and negative value for cooling) (W)

5.1.2 Mathematical formulation

To predict the indoor temperature of the building the following heat transfer equation based on the model described before is used:

$$\frac{dT_{in}(t)}{dt} = \frac{1}{R \cdot C} \cdot \left(T_{out}(t) - T_{in}(t)\right) + \frac{1}{C} \cdot \left(\alpha \cdot q_{rad}(t) + \beta \cdot q(t)\right)$$

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Where two additional parameters, α and β, have been added to the equation to consider the impact of the solar radiation and the HVAC system on the indoor temperature and t represents time (s). The resulting differential equation can be approximated by the next equation (where h is the sampling time of the data and k the step number):

$$T_{in}(k) = \frac{h}{R \cdot C} \cdot T_{out}(k-1) + \left(1 - \frac{h}{R \cdot C}\right) \cdot T_{in}(k-1) + \frac{h}{C} \cdot \left(\alpha \cdot q_{rad}(k-1) + \ \beta \cdot q(k-1)\right).$$

The previous equation can be simplified by defining simplified factors as follows:

$$T_{in}(k) = \omega_1 \cdot T_{out}(k) + \omega_2 \cdot T_{in}(k-1) + \omega_3 \cdot \left(\omega_4 \cdot q_{rad}(k-1) + \ \omega_5 \cdot q(k-1)\right),$$

where:

$$\omega_1 = \frac{h}{R \cdot C};\ \omega_2 = 1 - \frac{h}{R \cdot C} = 1 - \omega_1;\ \omega_3 = \frac{h}{C};\ \omega_4 = \alpha;\ \omega_5 = \beta.$$

These factors can be estimated applying linear regression to historical data. Then, the thermal parameters R and C, can be calculated as:

$$C = \frac{h}{\omega_3};\ R = \frac{h}{C \cdot \omega_1}.$$

Finally, indoor temperature can be estimated using the outdoor temperature and solar radiation predictions, together with the HVAC system operation plan.

5.1.3 Flexibility estimation and optimization

Assuming that the indoor temperature of the building can be predicted using weather forecasts and HVAC system operation plan, the energy cost of the HVAC system required to keep the indoor temperature within comfort levels is suitable to be optimised or used for flexibility purposes. For example, the problem may be defined as a mixed integer programming (MIP) problem, using as binary variables the switching on and off the HVAC system in every time step (*stateHeat* and *stateAir*). The optimisation problem can be used to reserve energy flexibility by increasing the lower temperature limit or reducing the upper limit.

The pseudocode of the MIP defined to optimise the HVAC system operation is shown below, including:

- An array of energy cost per hour (c).
- The range of comfort temperatures [Tmin, Tmax].
- Different arrays with the slopes per hour when the HVAC is cooling (slopeAir), heating (slopeHeat) and off (slopeOff). Temperature slopes are a simplification of the thermal model to transform the problem into lineal.

```
min
```

$$\sum_{i=1}^{n} (c_i \cdot stateHeat_i + c_i \cdot stateAir_i)$$

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$$
\begin{aligned}
\texttt{S.T.} \quad & T_0 = Tinit \\
& \forall\, i \; in \; 1, \dots, n : \\
& T_{i+1} - T_i = slopeHeat_i \cdot stateHeat_i \\
& \qquad + slopeAir_i \cdot stateAir_i \\
& \qquad + slopeOff_i \cdot (1 - stateHeat_i) \\
& stateHeat_i + stateAir_i \leq 1 \\
& Tmin \leq T_i \leq \mathrm{T}max \\
\texttt{and} \quad & stateHeat \in [0,1]^n , stateAir \in [0,1]^n \\
& and \; T \in \mathbb{R}^n
\end{aligned}
$$

Finally, as recommendation to be considered, if at any time step the model prediction does not match the real data, the model should be automatically recalibrated, and the HVAC system operation plan is updated according to the new conditions.

5.1.4 Performance tests and preliminary results

To test the performance of the prediction model, an existing dataset containing several days of thermal data from a building in Trondheim, Norway [72] has been used.

First, the 1R1C grey-box model is trained with the data from the dataset to fit the thermal parameters of the building. Then, one day's data is chosen to compare the real and estimated temperatures using the root mean square error (RMSE). Figure 5.2 shows the comparison between the measured indoor temperature of the building and the indoor temperature estimated by the model. In this example, the RMSE between the prediction and the real temperature is 0.071086, which means that a 1R1C model can predict the indoor temperature successfully.

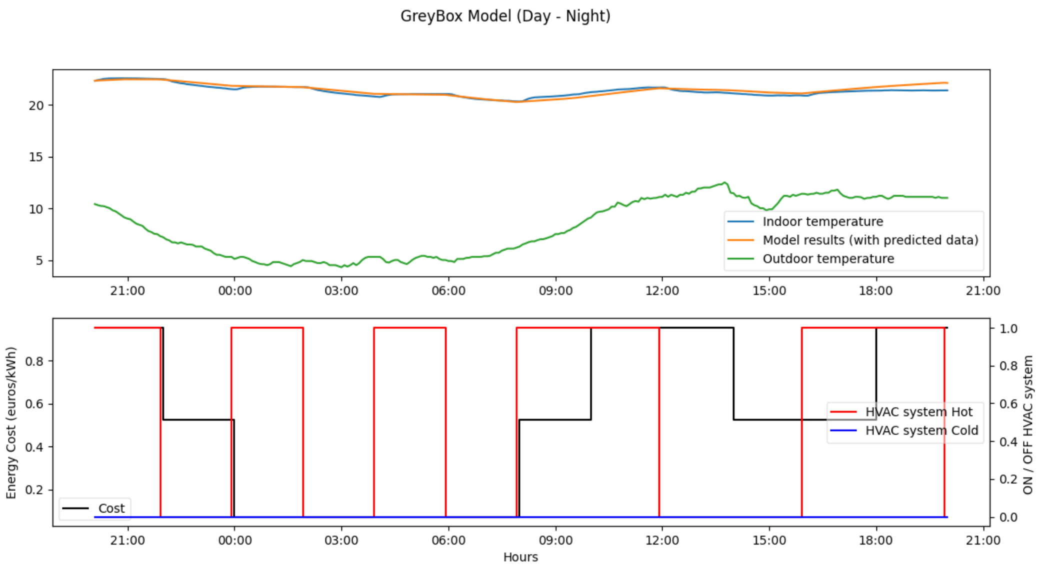

Figure 5.2 Comparison between real and model prediction indoor temperature

This prediction is used to obtain a cost-optimised operation plan for the HVAC system as shown in Figure 5.3.

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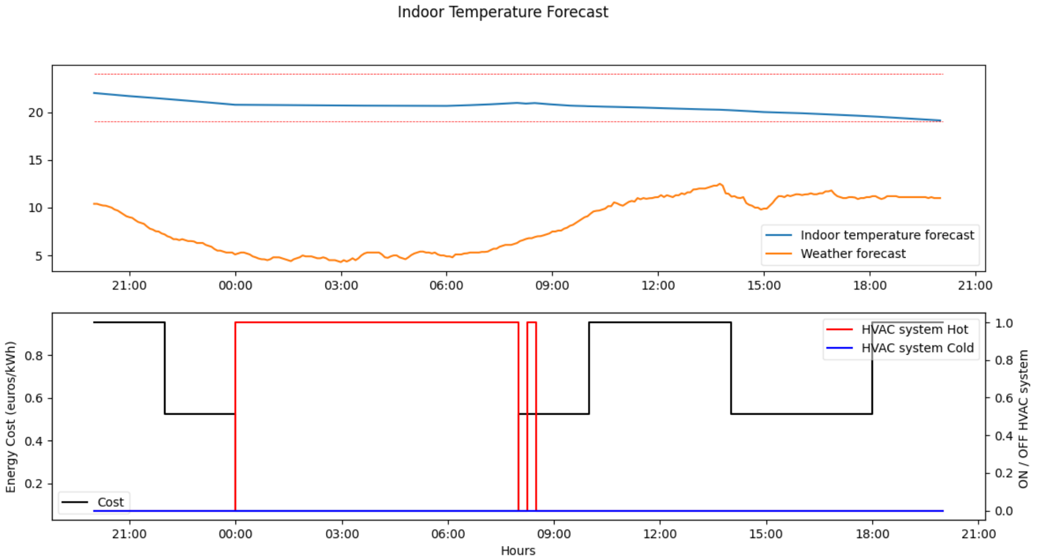

Figure 5.3 Initial HVAC system operation plan

Finally, a test including some temperature disturbances (such as window opening) was carried out. In that case, the model is recalibrated when it finds a mismatch between the estimated and the real indoor temperature, and the operation plan of the HVAC system is updated as shown in Figure 5.4.

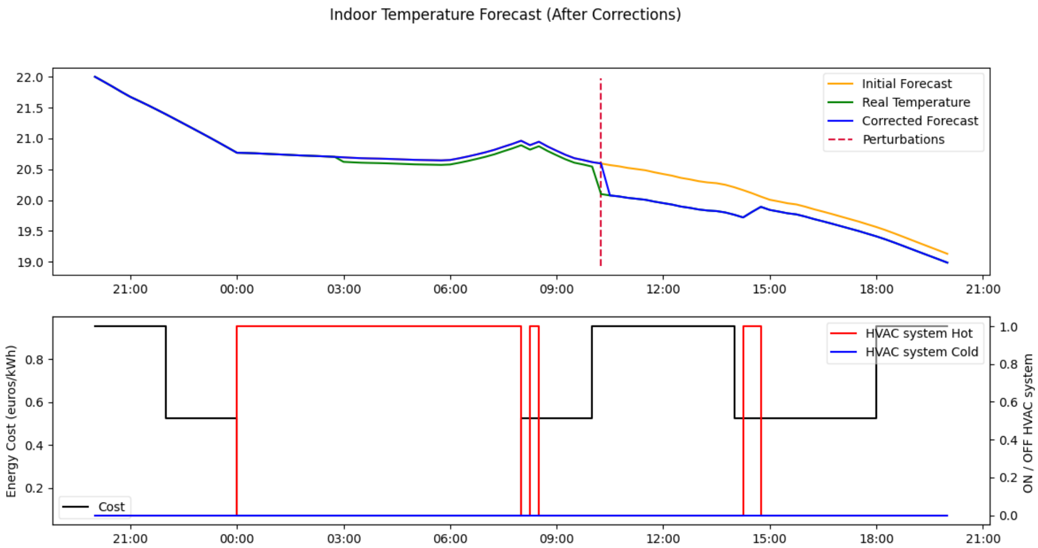

Figure 5.4 Updated HVAC system operation plan

This example demonstrated that a simply 1R1C model with historical data can offer a good estimation of indoor temperature evolution, what it is very useful to estimate the available flexibility and optimise HVAC operation. Given these electric models can be combined, it can be easily adapted to different building configurations.

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5.2 Building flexibility estimation: fuzzy logic

As mentioned before, one of the complexities of flexibility forecasting is to calculate the remaining flexibility and the energy profile after a flexibility activation event, when the system (building facilities) must manage to fulfil with setpoints. This means that the energy that is not used due to some interruption, will be used later. The question is, how much the energy flexibility activation modifies the energy profile later on? In this section, a fuzzy logic approach is used to estimate the remaining energy flexibility after an activation event in a building with PV system and a battery energy storage system (BESS).

Assuming that energy demand and renewable energy source (RES) generation forecasts are accurate enough, and the battery charging cycle is known, the daily flexibility estimate for a building can be obtained easily with the sum of RES generation, battery energy availability and building demand. Building demand is considered as a negative value, while RES generation and battery energy availability are considered as a positive value. Therefore, the energy flexibility estimation is represented with the following equation:

$$F = RES + Battery + Demand$$

The result of this equation may be negative, indicating that our consumption is greater than the energy availability given by RES generation and the battery. If so, the demand should be covered by the electric grid. However, the value ranges of these energy sources may differ from one building to other and to apply the fuzzy logic algorithm in any location, it is necessary to consider the maximum (rated) power of the target building to normalise data values.

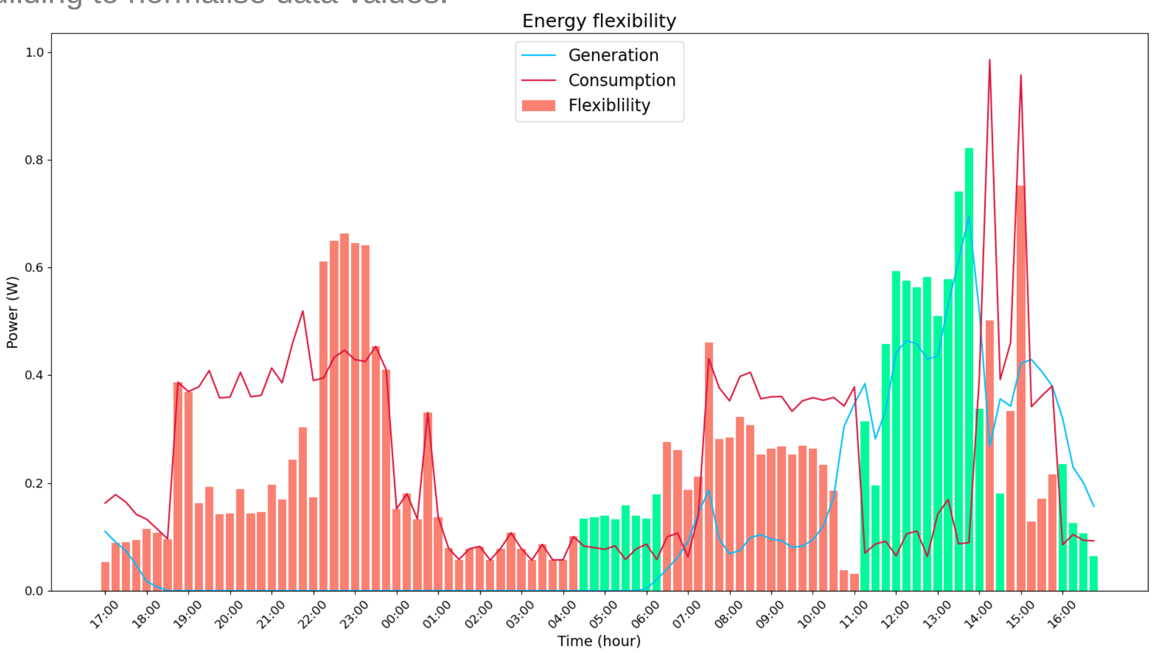

Figure 5.5 24-hour flexibility simulation.

To check the estimation using a fuzzy logic algorithm, a 24-hour simulation was carried out. For this purpose, data of the building demand [73] the state of charge of a battery [74] and RES generation [75], were used. The data is taken in time steps of 15 minutes along the day. In case the data is available with a smaller time step, the algorithm resamples the data by interpolation, adjusting it to the predefined number of samples.

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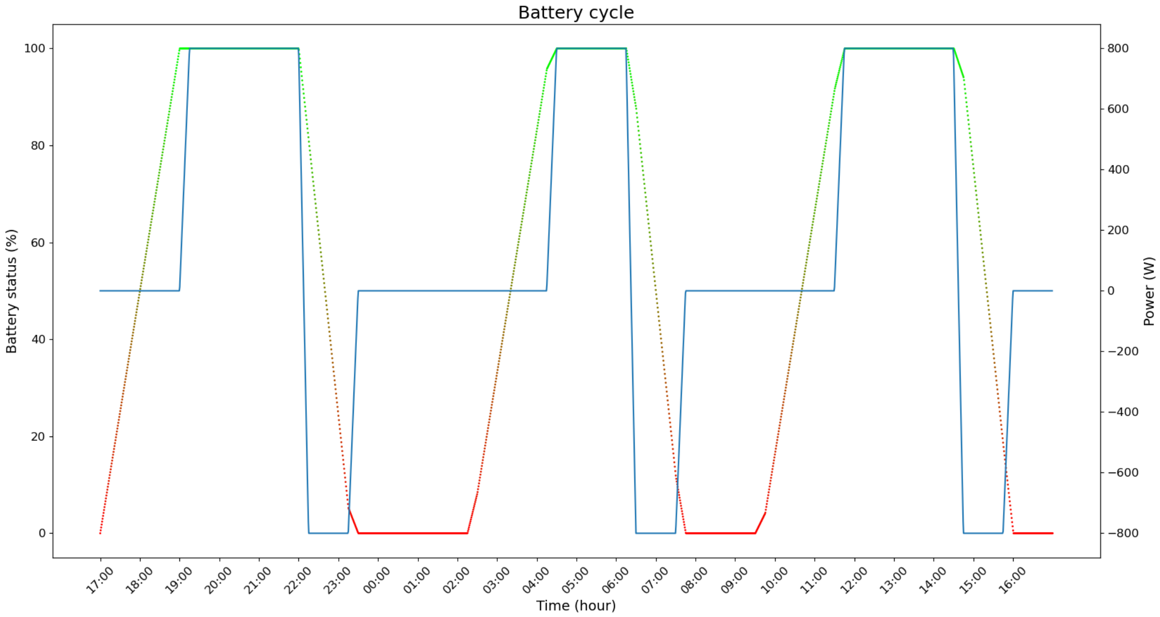

Figure 5.6 Battery cycle profile

Figure 5.5 shows the 24-hour simulation obtained for generation and demand profiles. These profiles allow to estimate the energy flexibility for next 24 hours. Flexibility is represented in the form of bars, indicating the red colour a negative flexibility and the green colour a positive one. As expected, during the night hours, the building flexibility is negative, indicating that the demand is greater than the generation. And over the day, there are several periods where the building provides a positive value of flexibility. In this simulation, the battery is assumed to complete 3 full charging cycles (Figure 5.6). The first cycle tries to cover the demand, while the second and third one represents the activation of flexibility in certain moment.

5.2.1 Algorithm development guidelines

Fuzzy logic control is a rule-based systems that generate outputs based on the magnitude and combination of inputs. For example, in case of some input is high then output is low. In this context the inputs used are 24-hour ahead prediction of RES generation, battery state of charge and expected demand. The outputs expected are the RES consumption, energy exchanged in the battery and the flexibility of the building.

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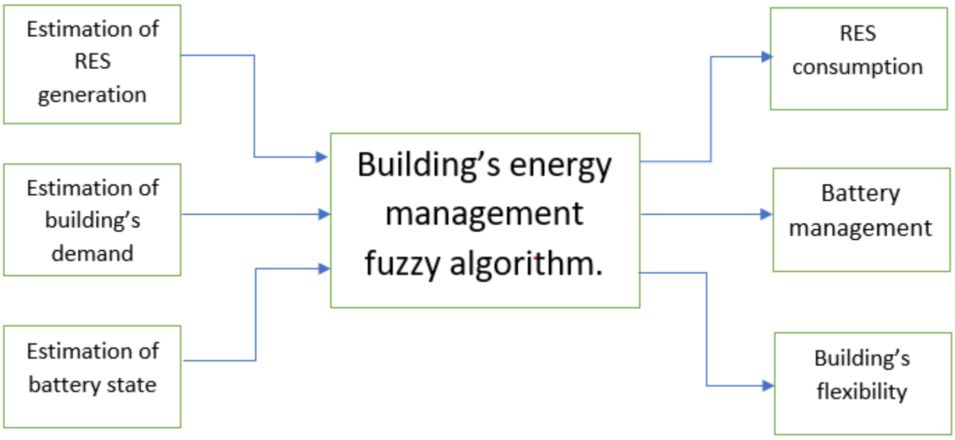

Figure 5.7 Flexibility management system based on fuzzy logic

The algorithm is designed to manage each building individually with some general rules. RES generation is prioritised to meet building's demand and, if possible, to charge the electric battery to get enough flexibility. In case of RES generation is not enough to meet building's demand, the electric grid will provide the remaining demand. Therefore, positive flexibility is given by RES generation and battery availability.

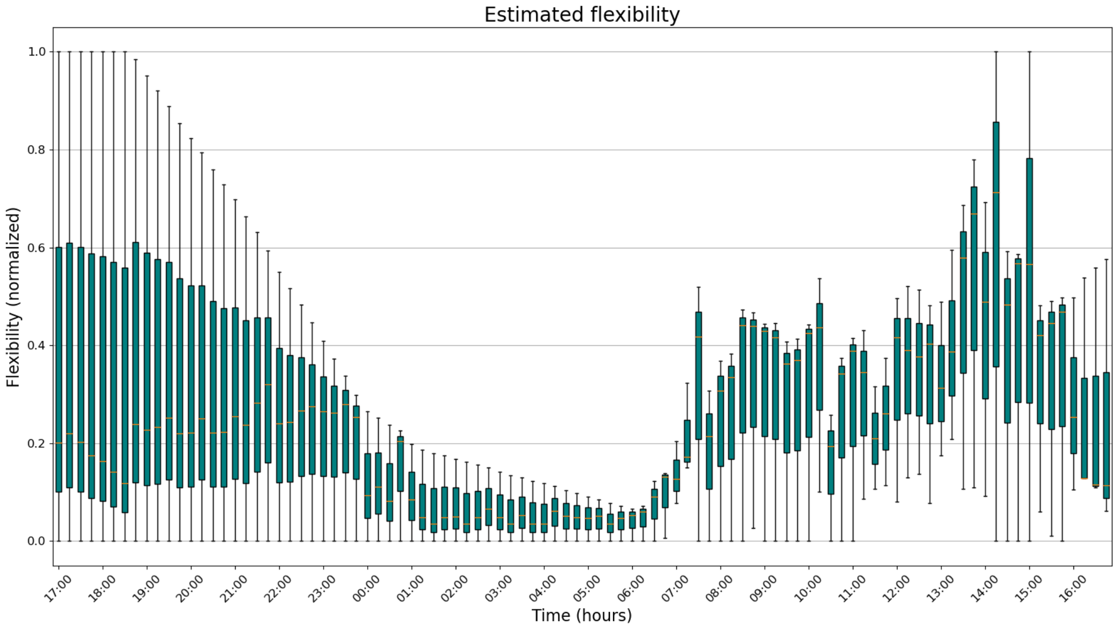

Figure 5.8 Example of flexibility availability (green bars) using fuzzy logic algorithm

Figure 5.8 shows the daily evolution of the flexibility, starting at 17:00. As the RES generation decreases, building's flexibility decreases and only the flexibility given by the battery is available. And when RES generation becomes available again, building's flexibility increases accordingly.

In this way, a potential energy aggregator system may request a target level of flexibility and the fuzzy logic system will react to meet the battery state of charge needed over the day. To emulate this process, it is considered that the aggregator requests whether the change should happen immediately or in the future, and if the activation of flexibility is positive (increase consumption) or negative (reduce consumption).

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Whenever a change is requested, the algorithm receives the input data, and it is executed for the indicated timestamp. As a result, the expected energy demand and the flexibility changes and the battery plan is restated considering that the energy demand (needs) of the building is fixed over the day, Therefore, the effect (ahead propagation) of the flexibility activation must distribute somehow the energy demand in next periods, prioritising those timeslots that, at first, presented higher energy flexibility. This rule can be implemented in different ways. For example, it can be considered a symmetric rule where the 20% of time slots that allow the greatest reduction/increase in consumption are prioritised.

Figure 5.9 shows the effect of flexibility activation at 20:45 is propagated and distributed towards more flexible hours. This flexibility activation request can be applied only when the daily plan (for example considering day-ahead market approach) is issued.

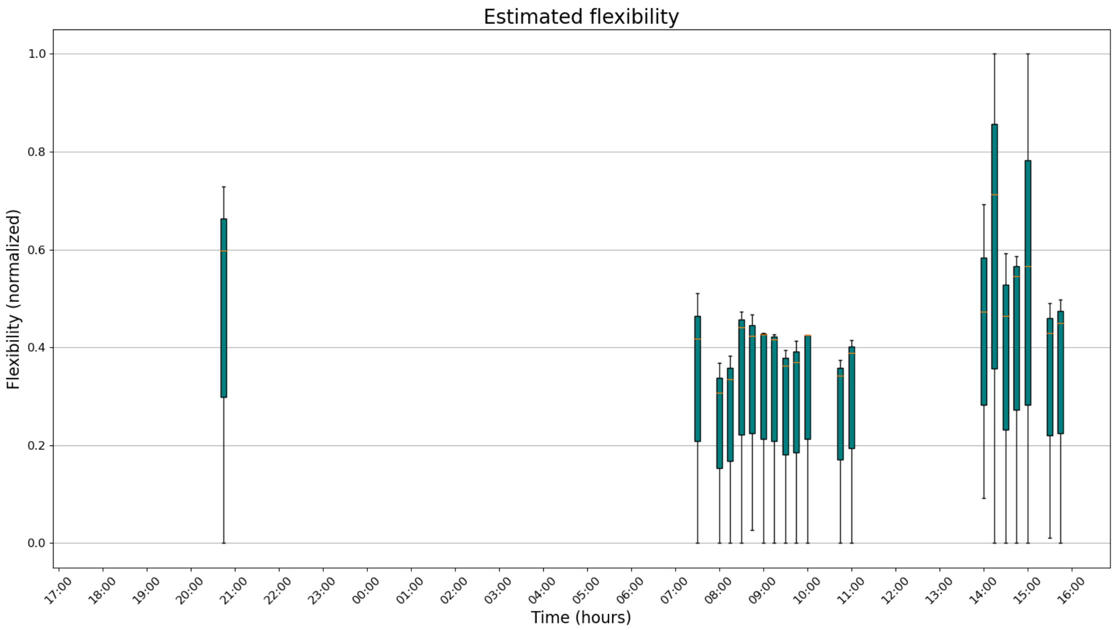

Figure 5.9 Effect of flexibility activation in next hours using fuzzy logic estimation

Fuzzy logic is a straightforward mechanism that allows checking quickly the effect of flexibility activation for specific users, reducing the complexity of calculations for scenario generation. Energy aggregators can quickly estimate the effect of their decision for energy flexibility activation. The rule to set the propagation effect can be adapted according to the characteristics and conditions of each customer (single factor) but it requires an additional supervision algorithm to establish the target value, and can be considered a different value for positive and negative flexibility periods. In this example, the factor was established at 20% based on the historical data given the battery and RES system capacity. However, this factor must be adapted for different weather conditions (RES generation) and occupancy profiles (expected demand).

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5.3 Building demand flexibility estimation: deep learning models

Achieving flexibility is one of the main challenges in smart grids. With the emergence of distributed energy sources and electricity pricing in time slots, the need for more intelligent management has arisen. Many works in the literature consider the correlation of attributes and time series for pattern recognition and prediction, such as deep learning techniques, the most used in the last years. The high performance of deep networks in many fields has led to their adoption for predicting flexibility [76]. For instance, deep learning models can detect complex energy patterns over time, such as the Long Short-Term Memory (LSTM) models.

Besides predicting flexibility, the realisation of an optimisation phase may be required to take the necessary actions to reach a set of targets (e.g., energy consumption). In this way, the optimization of the system can be addressed using a multi-agent approach [77]. This approach will allow not only to determine the necessary actions (e.g., discharging batteries, taking energy from cars) to reach the set objectives, but also to model the system on non-occurring situations to predict future behaviours.

The agent-based optimization will produce an active policy according to the grid available actions, being able to assess the consequences of those. Once the system goals have been established, the system will obtain the action succession that maximizes the system efficiency and increase the flexibility, according to the desired objective.

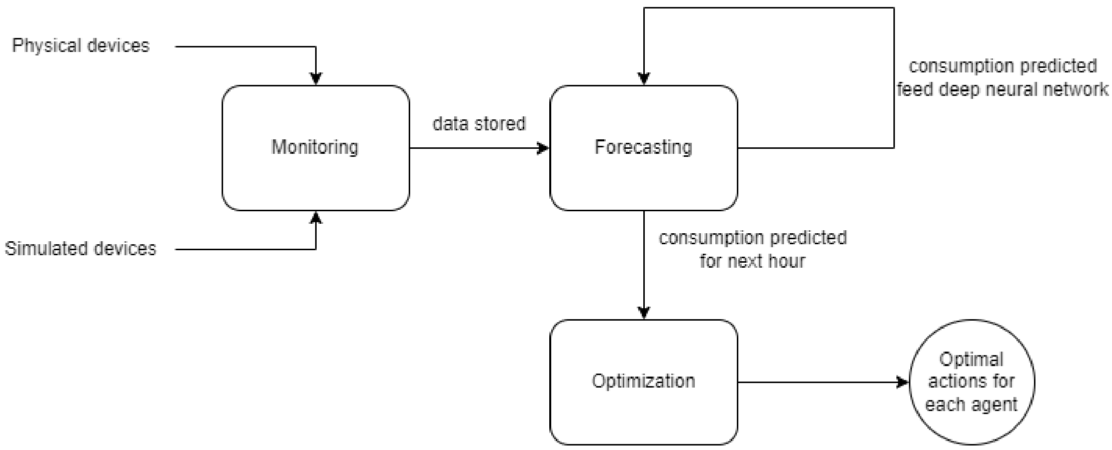

Figure 5.10 Agent-based platform Architecture

The proposed approach considers a multi-layer system, comprising a flexibility and consumption prediction layer based on deep learning techniques, and an optimisation layer based on multi-agent systems to both continuously predict and optimise the state of the smart grid, as shown in Figure 5.10. These two approaches comprise a closed loop, where each approach feeds on the data provided by the other, improving their accuracy after each iteration and optimizing the system.

These two approaches will be detailed as follows.

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5.3.1 Demand flexibility forecasting using Deep Learning

For the learning process of the flexibility algorithms, data retrieval and the creation of continuous datasets are necessary requirements. Hence, the first step in this layer is to monitor all available components. For this purpose, each available component in the smart grid (e.g., energy meters, batteries, solar panels, and charging points) will be monitored using the corresponding protocol (e.g., Modbus, TCP/IP), and all the information obtained will be stored into a database for continuous refinement and optimization and dispatched through data streams. Online learning will be considered for the continuous learning process of deep learning algorithms using data streams.

For those to which access or the component is not available, a deep learning algorithm will emulate the component behaviour as closely as possible when data or related input features are available. Physical-based models will be also considered for modelling the behaviour of some grid components. Therefore, this approach would allow the platform the possibility to explore and predict other components without the physical component availability, just with their simulation in the form of a digital twin developed with deep learning techniques, evaluating their behaviour in response to certain inputs. This prediction layer, therefore, has **two main objectives**: i) on the one hand, **to predict global aspects of the smart grid such as flexibility and consumption** based on the continuous monitoring and characterisation of its components; ii) and on the other hand, **to model grid components that are not available in a timely manner or for which no information is available** through the co-relation of variables and historical data and the use of physical models, which will allow us to have a better knowledge of the entire system and be able to carry out more accurate simulations of its behaviour.

Once data stream is available, continuous, and online learning of different deep learning models (e.g., LSTM, N-BEATS, DeepAR) with their respective optimizations and data pre-processing techniques will be explored. It is known that the grid data can fluctuate with a similar curve every year during the different seasons, therefore seasonality will be considered, and data will be collected throughout the year for optimal data handling.

For the lifecycle management of deep learning models, our Kafka-ML platform [78] will be used. Kafka-ML is an open-source[1] architecture that manages the pipeline of Artificial Intelligence (AI)/Machine learning (ML) models through data streams. Kafka-ML presents a paradigm shift in ML/AI from static and traditional datasets used in ML/AI into dynamic and continuous data streams, offering an open, user-friendly, and ready-to-use platform to the community that allows managing ML/AI pipeline steps such as the inference deployment in productions environments. Through this platform, continuous training and deployment of models will be enabled as information is received. Historical data will be used to continuously improve the deep learning models.

5.3.2 Optimizing system policy using multi-agent-based system

[1] https://github.com/ertis-research/kafka-ml/

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The multi-agent approach offers the possibility of solving optimization problems involving one or more agents that communicate with each other, and where their actions have repercussions on the others, thus requiring a strategy that optimizes their behaviour. They behave similarly to human interactions and allow solving optimisation problems in a satisfactory way in many cases. This approach has been demonstrated to be successful in addressing smart grid challenges [4], [5]. In this case, the multi-agent approach will allow the system to optimise and identify the actions to be carried out in the smart grid to meet the flexibility objectives established, as well as simulating unseen system behaviour.

One of the advantages of using multi-agent-based systems is that the problem can be detailed as much as desired, being possible to start from an approach where the building is worked as an agent to end up with decomposition in a set of agents of specific grids components, allowing the problem to be decomposed incrementally. This requires the definition of each agent, their actions, and results.
When defining the agents and their corresponding behaviour, it is necessary to identify those that can perform actions and can participate in the platform. The following agents and actions have been identified for the time being but are not limited to:

- Building: The building/centre will be the main component to model the flexibility and consumption of the smart grid. The actions that will be able to carry out are to increase/decrease the temperature of the rooms and turn off the air conditioning for reducing the energy consumption.
- Storage batteries: The batteries will provide additional energy to the building and can reduce consumption in those time slots of higher demand or cost. Their actions will be to charge or discharge the battery.
- Photovoltaic panels: Panels will provide energy consumption to the system. Depending on the needs of the system, its power can be controlled.
- Charging points: Charging points allow electric vehicles to be both charged and discharged from the grid in times of need. Therefore, the actions to be carried out will be to charge or discharge the vehicles.

To specify the behaviour of the agents, a policy needs to be defined. The objective of the policy is to obtain a valid actions sequence to carry out during the multi-agent execution. Policy optimisation allows agents to take better actions, thus improving the overall optimisation of the system. The application of deep learning has also been successfully demonstrated in this context [79], [80], especially deep reinforcement learning. Its main feature is that it does not require an accurate policy to obtain the best combination of actions, being able to start from a random policy and get optimal solutions. Moreover, this technique enables to explore many states faster than others, converging earlier to optimal solutions.

6 Conclusions and next steps

The current state of the art demonstrated that there are different strategies to estimate and manage customers energy flexibility but there is not a common approach to measure, estimate and manage this for future flexibility markets.

The steering signal proposed in chapter 3 will be used and tested in demo sites (Spain, Italy, and France). This effort has been done due to the unclear and unofficial definition

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of energy flexibility to be considered a commodity for future flexibility markets. The aim of this definition is to propose and create a trust environment where, customers, aggregators, and market regulators, can operate with transparency and low uncertainty, especially supported by forecasting algorithms.

The algorithms and mechanisms described in this document are still a work in progress in the context of ebalance-plus project. Based on the preliminary results, it is identified in which demo sites can be tested but have not been validated with real data. Therefore, this document will be restated according to the results obtained after the demonstration phase.

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