Flexible energy systems Leveraging the Optimal integration of EVs deployment Wave

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Local Aggregation and Cluster Coordination Tool

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List of Acronyms

Acronym	Meaning
API	Application Programming Interface
BES	Battery Energy Storage
BTM	Behind-the-Meter
CHP	Combined Heat and Power
CPO	Charging Point Operator
DER	Distributed Energy Resource
DSO	Distribution System Operator
DA	Data Aggregator
EA	Energy Aggregator
EMS	Energy Management System
EMSP	Electro-Mobility Service Provider
EV	Electric Vehicle
EVSE	Electric Vehicle Supply Equipment
FTM	Front-the-Meter
HP	Heat Pump
ICT	Information and Communication Technologies
ITS	Intelligent Transport System
UCD	University College Dublin
LV	Low Voltage
MG	Microgrid
MMG	Multi-Microgrid
MV	Medium Voltage
RT	Real-Time
SOC	State-of-Charge
TSO	Transmission System Operator
V1G	Grid-to-Vehicle
V2G	Vehicle-to-Grid
V2X	Vehicle-to-Everything
VGI	Vehicle-Grid-Integration
WP	Work Package

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Executive Summary

This deliverable (D4.5 “Local aggregation and cluster coordination tool”) documents the work carried out in work package 4 (WP4), Task 4.5 “Coordination and aggregation with surrounding assets”. This task was designed to produce strategies capable of harnessing the inherent flexibility offered by Vehicle-to-Everything (V2X) assets situated closely.

As the adoption of Electric Vehicles (EVs) accelerates, the demand for sufficient charging infrastructure becomes increasingly critical. Today, we can already witness the emergence of high charger densities in many European cities. The V2X-capable bidirectional chargers present a set of opportunities for the entities operating them such as enhanced power supply security through the provision of backup power and support for islanded operations and increased energy autarky, fostering greater self-consumption of local generation. V2X-flexibility can be integrated into the aggregation environments comprising other flexible assets such as Battery Energy Storages (BESs) and Combined Heat Power (CHP) to achieve a higher level of controllability in the face of the uncertainties arising from renewable power generation and inflexible electrical loads.

Flexible distributed energy resources (DERs) can be managed in an aggregated manner to optimize their performance and benefits. In the distribution segment of the power system, which consists of medium- and low-voltage grids, flexible DERs can be clustered into two aggregation levels: behind-the-meter (BTM) and in front-of-meter (FTM). While these DERs are often located behind the meter (i.e., coupling point of an energy consumer to the public grid), the impact of multiple BTM systems’ operation couples in FTM due to shared grid infrastructure. For example, excessive power consumption of EV chargers located in a specific BTM unit affects the power flows in the public grid that supplies power to other consumers as well. Therefore, Task 4.5 extends the local optimization perspective to larger ecosystems comprising multiple V2X-capable clusters (e.g., multi-microgrids with bidirectional EV charging units and MV distribution grids with multiple LV feeders comprising charging infrastructure) within a certain physical proximity. This expansion of scope recognizes that the effective coordination and management of V2X assets must transcend the boundaries of individual consumers. By doing so, it addresses the complex interplay of resources, demands, and grid interactions that occur at the distribution level.

To coordinate the operation of flexible assets at both BTM and FTM (i.e., front-of-the-meter) levels, it is possible to leverage two essential dimensions of flexibility within V2X-capable clusters: temporal and spatial. Temporal flexibility, in essence, represents the capacity to reshape power consumption profiles over time. This dimension is empowered by the ability to control and influence the timing and magnitude of Grid-to-Vehicle (V1G) and Vehicle-to-Grid (V2G) energy transfer. On the other hand, spatial flexibility is the capacity to redistribute power consumption across various parts of the shared grid infrastructure. To harness spatial flexibility effectively, one can strategically direct EVs to the most suitable sections of the distribution grids.

The research carried out in Task 4.5 produced a holistic view on coordination strategies for both individual BTM systems comprising several flexible assets including EV chargers and multiple V2X-capable BTM systems coupling in FTM, exploiting both temporal and spatial dimensions of V2X-

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flexibilities to reduce local grid congestion and improve the EV users' experience through reduced charging costs and charging time. This document:

- Identifies the functional and non-functional requirements for coordinating flexible assets' operation and introduces BTM and FTM coordination strategies that can be implemented to optimally align V2X-flexibility with cooperative goals.
- Presents a case study that assesses the impact of one of the introduced FTM flexibility aggregation strategies (i.e., optimized allocation of incoming EVs to one of the BTM charging sites) in campus network of University College Dublin (UCD) concerning two specific objectives defined by the FLOW project: alleviate grid challenges and improve user experiences.

This document is organized as follows. Section 1 provides an overview of the state-of-the-art in the area of energy flexibility management and highlights the focus of the research conducted within Task 4.5 of the FLOW project. Section 2 defines the functional and non-functional requirements to optimally exploit flexibility potential of DERs aggregated in V2X-capable BTM and FTM systems. Sections 3 and 4 formulate several BTM and FTM flexibility clustering strategies as mathematical decision models and define the concept architectures required to implement them. Section 5 presents the case study conducted in the UCD campus to quantify the impact of the FTM flexibility aggregation strategy (i.e., optimized allocation of incoming EVs).

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1. Background

1.1. State-of-Art and Research Positioning

The proliferation of charging infrastructure imposes a significant change in the urban landscape, reshaping the way the transport and energy systems interact. This rapid transformation of urban environments underscores the urgency of developing strategies to integrate EVs into existing energy grids while optimizing their use as valuable flexible assets. The research conducted within the scope of Task 4.3 “Advanced flexibility management system description and functionalities” underscores the need for operational strategies to address the needs of the entities operating charging infrastructure such as minimizing the charging costs for an EV fleet or maximizing the profit potential of the aggregator in the ancillary service market. This is required not only to address the growing challenges posed by EVs on power grids but also to elevate the role of V2X technology as a cornerstone in the transition towards a sustainable energy future.

The authors of [1] define flexibility "*a system's ability to provide secure and economical supply-demand balance across spatial and temporal scales by leveraging and seamlessly coordinating various controllable assets*". There exists a wide range of publications that coordinate the operation DERs for enhancing grid resilience, maximizing the share of renewable resources, minimizing the energy bills for consumers. The diverse nature of flexible resources and their complementary characteristics necessitate the clustering of these assets to unlock their full potential in addressing complex urban energy challenges. The clustering can be done in various legal and locational forms.

A Virtual Power Plant (VPP) is a centralized system that aggregates and optimizes the operation of numerous DERs connected to different geographical points of the grid. When a VPP incorporates energy storage and demand response capabilities, a large collection of DERs can act as a large dispatchable power generation source [2]. This approach does not require physical proximity in clustered DERs. On the contrary, Local Energy Community (LEC) is a collective of energy consumers, located within a specific geographical area, who come together to manage and share energy resources more efficiently. LECs aim to optimize energy production, consumption, and distribution, often incorporating renewable energy sources, energy storage, and demand response technologies. LECs have been attracting growing interest in the European energy landscape as they offer prosumers exchange energy and flexibility locally to maximize local consumption of renewable resources. A recent case study [3] estimates that LEC operation can eliminate 80% of violations of the safe voltage limits within LV distribution grids, demonstrating the potential of ensuring grid reliability with an operational measure as an alternative for otherwise mass grid extension. However, this should still be deeply analysed in real pilots.

Microgrids (MGs) represent another clustering approach, primarily focusing on coordinated control of BTM distributed energy resources for enhanced energy management and resilience. The technical literature provides a wide variety of operational management techniques for DERs in MGs as well as open-source tools for implementing effective load-balancing strategies in MGs [4]. MGs have garnered significant attention for integrating EVs as smart grid flexibility resources. This growing interest is partly due to the enhanced controllability that MGs offer in smaller, localized systems, which is a significant advantage over traditional grid structures. This controllability can help alleviating the challenges of integrating EVs into contemporary power systems [5].

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As presented in FLOW's D1.2 "Internal Baseline", the notion of EV flexibility encompasses the idea of *an EV's ability to adjust or curtail its power output at a specific location for a defined duration, leveraging its battery's storage capacity* [6]. In this context, EVs can be utilized in a versatile manner to carry out various tasks. There exists a large body of literature on EV charging management strategies exploiting temporal flexibility. However, the strategic allocation of EVs to optimal charging locations can also offer substantial advantages. For example, by intelligently directing EVs with urgent charging requirements to areas with excess capacity, it becomes possible to better manage overall demand on the system. Conversely, guiding EVs with high State-of-Charge (SOC) levels or those expected to remain parked for extended periods to congested areas can serve a dual purpose. These vehicles not only have the potential to discharge stored energy to alleviate grid congestion but also offer valuable assets, potentially generating returns for their owners through strategic positioning and energy discharge. This dynamic approach to EV placement and energy management holds the promise of introducing a new dimension to the role of EVs in the broader energy landscape. A recent publication [7] suggests a decentralized approach for managing the charging site allocations of the EVs in urban areas with multiple BTM units. Nevertheless, there is a significant untapped potential in fully leveraging the mobility of EVs to enhance the benefits of BTM and FTM flexibility aggregation.

This document serves as a central resource encompassing key techniques for coordinating both BTM and FTM flexibilities, including bidirectional charging, within neighboring energy systems. It provides comprehensive insights into various strategies and technologies aimed at optimizing the utilization of DERs and enhancing grid management. By addressing the challenges and opportunities associated with the integration of EVs and flexible assets into contemporary power systems, it provides the researchers, industry stakeholders, and decision-makers striving to navigate the evolving landscape of urban energy management and sustainability with valuable references.

1.2. Specific Objectives Supported in FLOW Project

Flexibility clustering is essentially the management of several flexible DERs in a coordinated manner. This is not necessarily confined with managing DERs owned by the same operator. Flexibility clustering at both BTM and FTM levels holds the potential to transform the urban energy landscape and promote the widespread adoption of electric vehicles, contributing to a more sustainable and resilient future. Corresponding local aggregation strategies contribute to three specific objectives pursued by the FLOW project: alleviating grid challenges, improving user experience, and increasing the supply potential of charging infrastructure. By supporting these specific objectives, this activity aims to be an active facilitator of energy transition.

The rapid proliferation of EV charging infrastructures has the potential to strain distribution grids, leading to voltage fluctuations and overloading in specific areas. However, BTM and FTM flexibility clustering strategies offer a promising solution to these challenges. By coordinating the charging and discharging of EVs within clusters, it becomes possible to distribute the load more evenly across the grid. This approach can alleviate grid stress, minimize voltage fluctuations, and enhance overall grid stability.

As the demand for EV charging services grows, it is imperative to upgrade the grid to accommodate additional demand. When the demand exceeds the capacity available in the grid, direct intervention to load may be required through local flexibility services or flexible connection agreements. This can

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translate into reduced supply to EVs. BTM/FTM flexibility clustering techniques enable the efficient utilization of resources such that the need for load curtailment is minimized. By dynamically allocating the loading capacity to different charging locations, the utilization of the existing system can be optimized. This results in a more robust and responsive charging network that serves EVs more effectively. Ultimately, increased supply potential ensures that EV drivers have access to reliable charging options, supporting the broader goals of decarbonization and sustainable urban transportation.

For the widespread adoption of electric vehicles, it is essential to enhance the user experience of EV owners. One critical aspect of this experience is the convenience and reliability of charging services. BTM/FTM flexibility clustering plays a pivotal role in this regard by optimizing the allocation of charging resources. When multiple BTM units are engaged in a flexibility aggregation program, the EVs' mobility can be exploited as a flexibility dimension. By strategically positioning EVs at charging stations — enabled by the local clustering beyond BTM units — with available capacity and ensuring efficient energy management, user satisfaction is improved. EV owners -who are instructed to the optimal charging location- experience shorter waiting times, reduced uncertainty about charging availability, and potentially lower costs. This, in turn, encourages more individuals to transition to electric mobility, contributing to a sustainable and user-friendly urban transportation ecosystem.

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2. Requirements of Flexibility Aggregation

Flexible DERs can be grouped at both BTM and FTM levels and coordinated for optimal management. By synchronizing the operation of clustered DERs, the system operation can be improved, and higher performance can be achieved in terms of grid congestion, charging cost minimization, integration of renewables etc. This section aims to describe *what the flexibility aggregation systems must do* (i.e., functional requirements) and *how they should perform* (i.e., non-functional requirements) to enable flexibility aggregation in BTM and FTM ecosystems.

2.1. Functional Requirements

This part lists the functional requirements of flexibility aggregation with surrounding assets. These functional requirements encompass the necessary features and capabilities that an aggregation system must possess to effectively perform its intended tasks and functions.

2.1.1 Field Connectivity

Field connectivity is a fundamental functional requirement for any Energy Management System (EMS). It entails the ability to establish reliable connections and exchange data between an EMS and intelligent assets in the field (BTM or FTM). In the context of V2X-flexibility clustering, it provides the aggregation/coordination system with essential capabilities, such as remotely access and collect data from DERs and EV charging stations, as well as send control signals and instructions to these devices.

The aggregation system must gather accurate real-time information on the status and availability of the EV chargers and other DERs to make accurate decisions. Let us consider a scenario where an EV connects to an Electric Vehicle Supply Equipment (EVSE) within a MG environment, which includes various non-flexible electricity consumers and a Photovoltaic (PV) system. The MG operator's primary objective is to maximize the self-consumption of locally generated energy, thereby minimizing dependence on external energy sources. When an EV arrives at the charging station, it possesses a specific energy demand for charging its battery and a certain degree of flexibility regarding the timing of its charging session — it can tolerate postponing its charging initiation within certain limits. The decision of whether to initiate the EV's charging immediately or delay hinges on the balance between electricity generation and consumption within the MG. For instance, if the PV system is currently generating surplus energy that exceeds the total local demand, it may be reasonable to expedite the EV's charging session to absorb this excess energy, thereby optimizing self-consumption. Additionally, the decision of "*how much to charge at this moment*" is influenced by the SOC of the EV's battery. Delaying the charging session excessively may result in reduced energy supply to the EV, potentially impacting its range and usability. Hence, the system responsible for clustering MG DERs (i.e., the MG EMS) must possess the capability to collect real-time data on the SOC of the EV's battery, and EV driver's inputs on charging preferences such as target SOC and estimate departure times

Besides making accurate decisions, the flexibility aggregation systems must be capable of implementing these decisions. This entails transferring the relevant information to the field devices in a practically understandable form within the respective time. Here, the communication protocols such as Open Charge Point Protocol (OCPP) and low-latency communication networks play important roles.

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2.1.2 Multi-Platform Interaction and Orchestration

V1G-V2G involves a complex interplay of actors, each with their unique objectives and constraints. EV drivers seek convenient and cost-effective charging solutions, CPOs want to maximize their profits, Electro-Mobility Service Providers (EMSPs) aim to improve user experience, and Distribution System Operators (DSOs) striving to maintain grid stability and reliability. When bidirectional chargers are clustered with surrounding assets, the ability of these diverse entities to *talk* in real-time (RT) and collaborate becomes paramount for seamless operation.

In the context of FTM aggregation, the stakeholders often need information that they do not directly monitor or own. For example, the power ratings of an EV's battery are not known by the CPO before the vehicle's connection to a charger while this information can help optimizing the use of flexible resources as it determines how much the V2G discharge capacity at a given time. Unlike the CPO, the EMSP, which is the first contact point of the driver in search of a charging spot, has this information in the respective register of its database. When the EMSP shares this information with the CPO properly in advance, the CPO can make more informed decisions on the charger allocation; it can reserve the chargers with proper V2G power rating to optimally exploit the flexibility. An infrastructure that allows for RT communication between the platforms of different stakeholders offers several advantages, including immediate response to grid conditions, consumption trends, and energy availability. However, mere communication is not enough; orchestration is equally crucial. The coordination between multiple intelligent stakeholders requires a well-defined logical sequence of activities so that each actor knows when they should decide, based on which data, and how they should inform the others.

2.1.3 Common Data Space

The FTM flexibility aggregation brings together multiple entities having their distinct objectives. The activities toward the community-oriented targets can affect these entities in non-uniform ways. For example, the grid-oriented allocation of incoming EVs into different BTM units could reduce avoidable stresses in highly loaded grid parts but it could also affect the revenues of the entities owning those BTM units. To properly track the consequences of cooperation activities, a common data space that can be accessed by all authorized beneficiaries is needed. Such a common data space not only serves the purpose of tracking outcomes but also serves as a valuable resource for developing data-driven solutions to address present and future challenges. With a wealth of data concentrated in one space, the potential for innovation and problem-solving in the energy ecosystem is greatly enhanced.

It is important to note that the common data space is also in line with the principles set by the EU Data Act that entered into force in 2024. The Data Act establishes clear and fair rules for accessing and using data within the European data economy- A common data space that provides a shared platform for data exchange between DER owners, aggregators, grid operators can support the achievement of the Data Act's goals for fostering data-driven innovation and value creation, by enabling the development and deployment of new solutions and services for optimizing the integration and operation of DERs in the energy system, contributing to the EU's green and digital transition.

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2.2. Non-functional Requirements

Non-functional requirements play a pivotal role in ensuring the overall effectiveness and reliability of the aggregation system in delivering its intended functions. These requirements go beyond the specific features and capabilities of the system and delve into aspects related to its performance, scalability, security, and data integrity.

2.2.1. Incentive Compatibility

When aggregating flexibility at the FTM level, achieving incentive compatibility stands as a paramount concern. Incentive compatibility ensures that the strategies and mechanisms put in place not only encourage collaboration but also provide tangible benefits to the involved parties. It involves designing frameworks where each BTM system operator, whether an energy producer, consumer, microgrid operator, parking lot operator, finds it in their best interest to actively contribute to the collective effort. In essence, incentive compatibility aligns individual objectives with the broader goal of optimizing energy resources and enhancing grid resilience. By fostering a sense of fairness and equitable rewards, it promotes trust and cooperation among stakeholders, ultimately driving the successful integration of flexible energy assets into the energy ecosystem.

Attaining incentive compatibility can be pursued through various avenues, and one key consideration is the entity responsible for setting incentives. In some cases, a regulated entity such as a local flexibility market operator or a DSO can take on the role of incentive setting. For example, a DSO having the capability to predict grid conditions in a particular area may establish corresponding local incentives to encourage collaboration among neighbouring assets. While this approach ensures that incentive settings are closely aligned with collaborative objectives and grid conditions, it may come with certain disadvantages, particularly concerning the preservation of free-market conditions. Alternatively, incentive setting can be entrusted to the broader market dynamics. However, this approach carries the risk of the market evolving into a state where incentives become non-collaborative, potentially undermining the collective effort to optimize energy resources and enhance grid resilience. Striking the right balance between regulated and market-driven incentive mechanisms is crucial to achieving incentive compatibility in the context of coordinating and aggregating flexibility among multiple BTM systems.

2.2.2. Scalability

As the energy landscape continues to evolve, the number of flexible DERs, including bidirectional chargers, BESs, CHP units, electrolyzers, and heat pumps (HPs), that could be coordinated is expected to grow significantly over time. With the prospect of incentives that make participation more appealing, an increasing number of consumers may be inclined to engage in these coordination efforts. However, this expanded participation also implies that the scale and complexity of coordination problems could become increasingly pressing, necessitating robust and scalable strategies to manage the burgeoning array of flexible resources within the energy grid.

In this context, scalability takes on heightened importance. The expansion in the quantity and diversity of flexible assets underscores the need for solutions that can seamlessly adapt and accommodate this increasing complexity. Scalability in the coordination and aggregation of these assets ensures that the

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strategies and tools developed today will remain robust and effective in case aggregation extends to a larger and more diverse ecosystem. This adaptability not only addresses the immediate challenges but also positions the energy sector to navigate the ever-expanding landscape of electric vehicles, decentralized energy generation, and emerging technologies. As a result, scalability becomes a critical attribute for the sustained success of flexibility coordination endeavours, serving as a foundational principle in the pursuit of optimized utilization.

2.2.3. Cyber Security

RT monitoring and control systems required for the utilization of flexible resources open a multitude of potential attack vectors that malicious actors can exploit. Each new device added to the flexibility aggregation ecosystem increases the vulnerabilities. With the devices becoming more interconnected, the attackers gain the opportunity to compromise larger systems. In such a landscape, the cybersecurity concern becomes paramount, making it imperative to safeguard the integrity and security of the Information and Communication Technology (ICT) ecosystem.

To address the growing cybersecurity challenges, it is crucial to maintain a robust security framework within the coordination and aggregation framework. This entails not only preventing and detecting potential attacks but also adopting a *resilient-by-design* approach. Adopting a resilient-by-design approach ensures that systems enabling coordination of flexible DERs and V2X-capable clusters incorporate backup routines to continue exploitation of flexibility potential even when a cyber-physical failure disrupts the normal workflow. This proactive approach is crucial for fortifying the collaboration against evolving threats and minimizing the potential impact of cybersecurity incidents.

2.2.4. Data Integrity and Sovereignty

As diverse assets and stakeholders participate in the coordination and aggregation of flexible resources, a substantial volume of data is generated and exchanged. The data array encompasses information on energy consumption, pricing signals, grid conditions, and more. Ensuring data integrity is paramount to guarantee the accuracy, consistency, and reliability of this information. For example, when two BTM entities have a bilateral capacity-sharing agreement, the transactions must be properly recorded. Any compromise in data integrity could have far-reaching consequences, leading to incorrect remunerations and suboptimal resource allocation, which can lead relevant stakeholders to refrain from collaboration. Therefore, robust mechanisms for data validation are fundamental components of any flexibility aggregation framework.

Moreover, the concept of data sovereignty is pivotal in the context of flexibility aggregation. It refers to the ownership and control of data, and it is a vital consideration as multiple stakeholders interact within the energy ecosystem. Each participant, whether a DSO, energy prosumer, or EV driver, may have distinct requirements and concerns regarding the sharing and access to their data. Maintaining data sovereignty means that stakeholders retain control over their data, deciding who can access it and under what conditions. This not only fosters trust among participants but also aligns with regulatory and privacy requirements. By implementing data sovereignty mechanisms, flexibility aggregation initiatives can facilitate collaboration while respecting the autonomy and preferences of individual stakeholders, ultimately contributing to a more transparent and equitable ecosystem.

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3. Flexibility Aggregation Behind-the-meter

The term BTM refers to the location of energy assets and resources within the customer's side of the electric meter. The assets of various types of consumers, such as residential, commercial, or industrial, can be aggregated BTM. Microgrids and parking lots can be considered typical BTM entities provided that the grid operator meters the net consumption of the entire facility rather than individual assets. Each of these assets such as EV chargers, BESs and multi-energy systems brings its unique capabilities to the overarching objective of flexibility aggregation, and thus plays a role in the pursuit of grid stability, user satisfaction, and cost-efficiency. This chapter focuses on understanding how different types of BTM assets can contribute to optimizing power consumption profiles to bolster grid stability, facilitate renewable energy integration, and enhance the overall performance of the energy system.

This chapter is organized as follows. Firstly, it identifies the key flexible assets that can support the operational goals of the BTM units incorporating EV chargers. Second, it presents a concept architecture that describes the interactions between the BTM EMS, flexible DERs, and external systems required for the cooperative operation toward the system goal. Thirdly, it introduces an operational optimization strategy that controls all flexible assets over a predefined scheduling horizon.

3.1. Flexible System Components

The BTM flexibility clustering can include a large array of assets. These assets can be broadly categorized into three main groups: (1) flexible electric load and generation, (2) electrical energy storage, and (3) multi-energy storage.

Flexible loads refer to electrical appliances or processes that can flexibly adjust their energy consumption timing without compromising their functionality. Examples include electric water heaters, industrial machinery, and certain Heating, Ventilation and Air Conditioning (HVAC) systems. By intelligently shifting their energy demand to off-peak periods, flexible loads can contribute to load balancing and reduce peak demand on the grid. A typical way of aligning their operation would be the postponement of non-urgent consumption to the hours of low EV demand. Flexible electric power generation sources encompass renewable DERs solar panels and wind turbines and fuel-based generators. Renewable DERs offer limited flexibility; since they are weather dependent, the possible control is unidirectional (i.e., curtailment). Nevertheless, their energy generation profiles can be adjusted to align with specific grid requirements or consumer preferences. For instance, when the grid connection of the BTM system does not allow power injection to the public grid or the grid code limits the volume of injection, the generation could be curtailed. Fuel-based generators are fully controllable. However, they cannot be considered green power sources. The flexible load and generation in the BTM premises can be operated in a way to support the objectives such as minimizing costs and emissions, and enhancing grid stability.

The main electrical energy storage devices are BES systems and EVs. BES systems represent the stationary facet of this category, securely positioned BTM infrastructure. In contrast, EVs embody the mobile dimension of electrical energy storage, continually traversing the urban landscape. This distinction lies in the fundamental nature of BES as a static BTM resource and EVs as dynamic, mobile assets. BES systems are quite efficient and simple to manage. EVs are equivalent to batteries from the electrical system point of view, which can serve the same purpose if both G2V and V2G are feasible.

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Their mobility adds a level of uncertainty to the equation; the EVs bring a dynamic element to the operational optimization problem.

Delving deeper into the landscape, a spectrum of multi-energy assets emerges, including CHP units, electrical HPs, and electrolyzers can support the operational objectives of the BTM systems. CHP units provide a multifaceted approach, simultaneously generating electricity and useful heat, enhancing overall energy efficiency. Their operations can be tailored to the needs of the remaining electrical power components. For instance, especially when they are supported with thermal electrical storage, the CHPs can generate power when EV consumption is high, reducing the net aggregate BTM load. Electrical HPs offer efficient heating and cooling solutions while contributing to flexibility through demand-side management. They can be operated to consume excess PV generation and thus help balancing the local generation with respective local consumption. Likewise, electrolyzers can convert excess electrical power into green hydrogen, which can be later added to fuel-cell cars or burnt as natural gas for heating purposes.

3.2. Concept Architecture

In the quest to harness the full potential of BTM flexibility, this document adopts the concept architecture introduced in a recent publication [8]. The authors of [8] refer to the entity that controls a set of DERs below a specific grid connection point as Renewable Energy Community (REC), which closely aligns with the notion of a BTM unit. Both terms essentially encapsulate the idea of clustering DERs behind a specific grid connection point. In essence, whether referred to as a REC or a BTM unit, the core scope remains the same: a localized grouping of assets that collectively contribute to grid flexibility and sustainability. Therefore, the adopted architecture meets the requirements for clustering V2X flexibility with other DERs BTM.

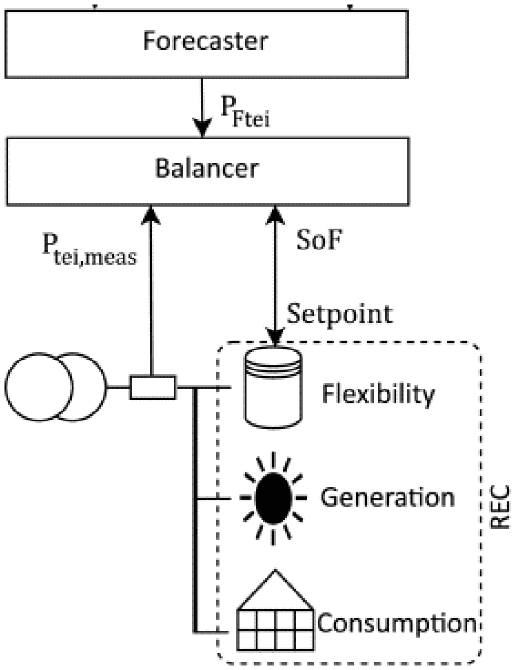

Figure 1. Schematic representation of the EMS managing BTM flexibilities [8].

Figure 1 provides a comprehensive visualization of the interactions between various functions within the EMS that controls the available storage and production capacities, all while adhering to a multitude of targets. At the core of this EMS ecosystem is the *Forecaster*, tasked with predicting the load and generation of the non-flexible assets in various timelines. These forecasts serve as indispensable input parameters for the *Balancer* function. The *Balancer* is the module responsible for managing the dynamic power exchange between the BTM unit and the public grid. It determines the set points of the flexible assets to achieve desired aggregate behavior. In the referred paper, this management aligns with the target of maximizing self-sustainability of the BTM unit. Therein, the ideal outcome would be measuring zero active power at the meter –denoted by $P_{tei,meas}$ in the figure and the following equation. However, when the BTM flexibility is utilized to support FTM goals or the BTM operator sees some arbitrage opportunities in the energy market, the *Balancer* can lead $P_{tei,meas}$ to time-varying profiles. A range of objectives such as maximizing the local consumption of the local generation, minimizing the emissions due to power production, and minimizing power bill can be obtained with optimized control of the DERs.

3.3. Optimization Model

3.3.1. Reference Model

The authors of [8] suggest a nonlinear optimization model to control power curves of flexible DERs over a scheduling horizon. The objective is to reduce energy exchanged with the public grid over a scheduling period T by assigning power consumption/injection set points to the flexible DERs with a sampling time of Δt. Depending on the available computation means and the length of the scheduling horizon (e.g., 24 hours), various Δt could be selected (e.g., 15 minutes and 1 hour). The objective function (3.1) penalizes both the power imported (P_{ti}^t) and exported (P_{te}^t). This model takes time-dependent forecast of the power consumption (P_{Ftc}^t) and generation (P_{Ftg}^t) of the non-controllable devices as input parameters. It represents the aggregate power consumption and withdrawal of flexible DERs at a given time t with two optimization variables, $P_{flex,ch}^t$ and $P_{flex,dis}^t$:

$$\min \sum_{t=1}^{T} \left(P_{ti}^t + P_{te}^t\right) \tag{3.1}$$

subject to

$$P_{ti}^t, P_{te}^t, P_{flex,dis}^t, P_{flex,ch}^t \geq 0 \tag{3.2}$$

$$P_{Ftg}^t + x_{dis}^t P_{flex,dis}^t + y_i^t P_{ti}^t = P_{Ftc}^t + x_{ch}^t P_{flex,ch}^t + y_e^t P_{te}^t \tag{3.3}$$

$$0 \leq x_{dis}^t, x_{ch}^t \leq 1 \tag{3.4}$$

$$0 \leq y_i^t, y_e^t \leq 1 \tag{3.5}$$

$$SOC^{t+1} = SOC^t - x_{dis}^t P_{flex,dis}^t \Delta t + x_{ch}^t P_{flex,ch}^t \Delta t \tag{3.6}$$

$$0 \leq P_{flex,dis}^t \leq P_{flex,max}^{dis}, \quad 0 \leq P_{flex,ch}^t \leq P_{flex,max}^{ch} \tag{3.7}$$

$$\underline{SOC} \leq SOC^t \leq \overline{SOC} \tag{3.8}$$

$$SOC^{t=0} = SOC^0 \tag{3.9}$$

Constraint (3.2) ensures that the variables for power import, export, charging ($P_{flex,ch}^t$), and discharging ($P_{flex,dis}^t$) are non-negative. Constraint (3.3) maintains equilibrium between generated and consumed power: generation forecast (P_{Ftg}^t), flexible discharge ($x_{dis}^t \cdot P_{flex,dis}^t$), and import $\left(y_i^t \cdot P_{ti}^t\right)$

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on the left side; consumption forecast (P_{Ftc}^{t}), flexible charge ($x_{ch}^{t} \cdot P_{flex,ch}^{t}$), and export ($y_{e}^{t} \cdot P_{te}^{t}$) on the right side. The binary nature of the variables x_{dis}^{t}, x_{ch}^{t}, y_{i}^{t}, and y_{e}^{t}, as defined in constraint (3.4), precludes the simultaneous occurrence of charging/discharging from the flexible assets and power import/export for each t. Constraints (3.6)--(3.9) pertain to the system's flexibility; constraint (3.6) describes the state of flexibility over successive intervals, considering a time step Δt, with SOC^{t} and SOC^{t+1} denoting the flexibility states at consecutive times. The maximum limits for charging ($P_{flex,max}^{ch}$) and discharging ($P_{flex,max}^{dis}$) power are specified in constraint (3.7), while constraints (3.8) define the acceptable flexibility state range with minimum ($\underline{SOC}$) and maximum ($\overline{SOC}$) values. The initial flexibility state ($t = 0$) is set by SOC^{0} in constraint (3.9). Notably, the parameters SOC^{0}, $\underline{SOC}$, and $\overline{SOC}$ are expressed as percentages of the total flexibility capacity $Flex_{cap}$, with a 100% SOC indicating full capacity availability. With all flexibility parameters and forecast profiles provided, the optimization model computes the optimal continuous and discrete variable values in line with the objective function (3.1).

3.3.2. Proposed Model

Despite the efficacy of the reference model, there are two notable limitations. Firstly, the model simplifies the collective behavior of various DERs by representing them as a single virtual storage unit. The optimization model incorporates three primary variables: one for charging ($P_{flex,ch}^{t}$), one for discharging ($P_{flex,dis}^{t}$), and another representing the state of the virtual storage (SOC^{t}). While reducing the problem size, this abstraction does not fully encapsulate the complex behaviors present in BTM systems compriing diverse DER types. For instance, the current model cannot differentiate scenarios where some EVs might be supplying power back to the grid while HPs concurrently draw power for heating. Secondly, this model has nonlinear constraints, increasing the computational burden. The non-linearity also limits the optimization solvers that can be deployed within the EMS. To accurately represent intricate dynamics of various types of DERs, the optimization model was modified as follows:

$$\min \sum_{t=1}^{T} \left(P_{ti}^{t} + P_{te}^{t} \right) \tag{3.10}$$

subject to

$$P_{Ftg}^{t} + P_{flex,dis}^{t} + P_{ti}^{t} = P_{Ftc}^{t} + P_{flex,ch}^{t} + P_{te}^{t} \tag{3.11}$$

$$P_{flex,ch}^{t} = \sum_{l \in L} P_{l}^{t} + \sum_{b \in B} P_{b,ch}^{t} + \sum_{v \in V} P_{v,ch}^{t} + \sum_{m \in M} P_{m}^{t} \tag{3.12}$$

$$P_{flex,dis}^{t} = \sum_{g \in G} P_{g}^{t} + \sum_{b \in B} P_{b,dis}^{t} + \sum_{v \in V} P_{b,dis}^{t} + \sum_{n \in N} P_{n}^{t} \tag{3.13}$$

$$0 \le P_{ti}^{t} < y_{i}^{t}\, \overline{P_{ti}} \tag{3.14}$$

$$0 \le P_{te}^{t} < y_{e}^{t} \overline{P_{te}} \tag{3.15}$$

$$0 \le P_{l}^{t} < \overline{P_{l}} \tag{3.16}$$

$$0 \le P_{g}^{t} < \overline{P_{g}} \tag{3.17}$$

$$0 \le P_{b,dis}^{t} \le x_{b,dis}^{t} \overline{P_{b,dis}} \tag{3.18}$$

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$$0 \leq P_{v,dis}^{t} \leq x_{v,dis}^{t} \overline{P_{v,dis}} B_{v}^{t} \tag{3.19}$$

$$0 \leq P_{b,ch}^{t} \leq x_{b,ch}^{t} \overline{P_{b,ch}} \tag{3.20}$$

$$0 \leq P_{v,ch}^{t} \leq x_{v,ch}^{t} \overline{P_{v,ch}} B_{v}^{t} \tag{3.21}$$

$$0 \leq P_{m}^{t} \leq \overline{P_{m}} \tag{3.22}$$

$$0 \leq P_{n}^{t} \leq \overline{P_{n}} \tag{3.23}$$

$$y_{i}^{t} + y_{e}^{t} = 1 \tag{3.24}$$

$$x_{b,dis}^{t} + x_{b,ch}^{t} = 1 \tag{3.25}$$

$$x_{v,dis}^{t} + x_{v,ch}^{t} = 1 \tag{3.26}$$

$$S_{b}^{t+1} = S_{b}^{t} - P_{b,dis}^{t} \frac{\Delta t}{C_{b}} + P_{b,ch}^{t} \frac{\Delta t}{C_{b}} \tag{3.27}$$

$$S_{v}^{t+1} = S_{v}^{t} - P_{v,dis}^{t} \frac{\Delta t}{C_{v}} + P_{v,ch}^{t} \frac{\Delta t}{C_{v}} \tag{3.28}$$

$$\underline{S_{v}} < S_{v}^{T} \tag{3.29}$$

To improve readability, a summary of the notation used within this model is provided in the following:

$T, \Delta t, t$	Scheduling horizon, sampling time, time step identifier ($t \in 0,1,..,T$)
L, l	Flexible load set and identifiers *($l \in 0,1,..,L$)*
G, g	Flexible generator set and identifiers *($g \in 0,1,..,G$)*
B, b	BES set and identifiers *($b \in 0,1,..,B$)*
V, v	EV set and identifiers *($v \in 0,1,..,V$)*
M, m	Set and indices of multi-energy storage units consuming power
N, n	Set and indices of multi-energy storage units injecting power
P_{Ftg}^{t}, P_{Ftc}^{t}	Parameter. Non-flexible DER's predicted generation and consumption at *t.* [kW]
$\overline{P_{ti}}, \overline{P_{te}}$	Parameter. Power import and export limits of BTM system. [kW]
$\overline{P_{l}}, \overline{P_{g}}$	Parameter. Consumption and injection limits of flexible loads and generators. [kW]
$\overline{P_{b,ch}}, \overline{P_{b,dis}}$	Parameter. Charge and discharge power limits of BESs. [kW]
$\overline{P_{v,ch}}, \overline{P_{v,dis}}$	Parameter. Charge and discharge power limits of EV batteries. [kW]
$\overline{P_{m}}, \overline{P_{n}}$	Parameter. Consumption and injection limits of multi-energy storage units. [kW]
C_{b}, C_{v}	Parameter. Energy storage capacity of BESs and EV batteries. [kWh]

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B_v^t	Parameter. Predicted position of EV (connected or away) at t. [Binary]
$\underline{S_v}$	Parameter. Minimim SOC that EV must reach by T. [%]
P_{ti}^t, P_{te}^t	Variable. Power imported and exported by BTM system to the public grid at t. [kW]
$P_{flex,ch}^t, P_{flex,d}^t$	Variable. Net power consumed and injected by the flexible DERs at t. [kW]
P_l^t, P_g^t	Variable. Power consumed and injected by flexible loads and generators at t. [kW]
P_m^t, P_n^t	Variable. Power consumed and injected by multi-energy storage units at t. [kW]
$P_{b,ch}^t, P_{b,dis}^t$	Variable. Power consumed and injected by BES at t. [kW]
$P_{v,ch}^t, P_{v,dis}^t$	Variable. Power consumed and injected by EV at t. [kW]
y_i^t, y_e^t	Variable. Status (importing and exporting) of BTM system at t. [Binary].
$x_{b,ch}^t, x_{b,dis}^t$	Variable. Status (charging and discharging) of BES at t. [Binary]
$x_{v,ch}^t, x_{v,dis}^t$	Variable. Status (charging and discharging) of EV at t. [Binary]
S_b^t, S_v^t	Variable. SOC of BES and EV at t. [%]

In the constraint set of the optimization model, P_{Ftc}^t, P_{Ftg}^t, $\overline{P_{ti}}$, $\overline{P_{te}}$, $\overline{P_l}$, $\overline{P_g}$, $\overline{P_{b,dis}}$, $\overline{P_{v,dis}}$, $\overline{P_{b,ch}}$, $\overline{P_{v,ch}}$, B_v^t, C_b, and C_v are input parameters. $\overline{P_{ti}}$ and $\overline{P_{te}}$ represent the import and export limits of the grid connection of the entity operating the BTM system. $\overline{P_l}$ and $\overline{P_g}$ are the power ratings of the specific flexible loads and generators. $\overline{P_i}$ and $\overline{P_j}$ are the maximum power consumption and injection that multi-energy storage units can support. $\overline{P_{b,dis}}$ and $\overline{P_{v,dis}}$ are the maximum discharge power of batteries and EVs, and $\overline{P_{b,ch}}$ and $\overline{P_{v,ch}}$. B_v^t is an input parameter having value of 1 for the t when EV is expected to remain connected to BTM charger. C_b and C_v represent the energy capacity of the BESs and EVs.

This new formulation replaces the variables representing the charging (i.e., net power consumption) and discharging (i.e., net power consumption) behavior of the virtual aggregated storage in the original model ($P_{flex,ch}^t$ and $P_{flex,dis}^t$) with the variables that represent each flexible DER's contribution to the overall balance. The flexible DERs are divided into several subsets comprising flexible electrical load (L), flexible electrical generation (G), batteries (B), EVs (V), and multi-energy storage units consuming power (M) and injecting power (N). The set M can include HPs and P2G electrolyzers while N comprises CHP units. As can be seen in (3.30), each l in L and each m in M contributes to $P_{flex,ch}^t$. Likewise, (3.13) shows that $P_{flex,dis}^t$ includes the contribution of all g in G and all n in N. As opposed to these unidirectional flexible DERs, BESSs and EVs can contribute to both sides of the overall power balance (3.11). However, a single stationary or EV battery can either be charging or discharging at once. Therefore, the model includes variables $P_{b,dis}^t/P_{b,ch}^t$ and $P_{v,dis}^t/P_{v,ch}^t$ to represent discharging/charging powers of BESSs and EVs explicitly. To ensure that $P_{b,dis}^t$ and $P_{c,dis}^t$ do not take non-zero value at the same t, binary variables $x_{b,dis}^t$ and $x_{b,ch}^t$ are inserted into the model. The constraints (3.18-3.21) and (3.25-3.26) jointly serve to model the exclusiveness between $P_{b,dis}^t$ and $P_{b,ch}^t$as well as $P_{v,dis}^t$ and $P_{v,ch}^t$.

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The only difference between the constraints pertaining to BESs and EVs are the presence of the binary parameter, B_v^t, in case of EVs. Since EVs are mobile DERs, the duration for which they can contribute to the power balance is limited. Likewise, the new formulation models the exclusiveness of import (i.e., BTM withdrawing power from the public grid) and export (i.e., BTM injecting power to public grid) cases with the help of two binary variables (y_i^t and y_e^t) in constraints (3.14), (3.15), (3.24). The new formulation adopts the approach original formulation uses to model the change of the state of the virtual capacity (3.6). However, the new model uses explicit constraints for each DER using electrical storage, namely (3.27) for BESs and (3.28) for EVs. To prevent the overexploitation of the EVs' flexibility, which could potentially lead to dissatisfaction among drivers, the constraint (3.29) is formulated to guarantee that the EV battery's SOC reaches a predetermined threshold ($\underline{S_v}$) at the end of the scheduling horizon, safeguarding the usability of the EVs post-optimization.

It is important to note that, the multi-energy DERs such as HPs, CHPs, electrolyzers are modeled to account for their production of other energy carriers like heat and hydrogen. The BTM system can directly consume or store these outputs in thermal storage systems or fuel cells. Since the systems can maintain the generation/consumption equilibrium to a certain degree, in practice, the parameters $\overline{P_m}$ and $\overline{P_n}$ are subject to change. However, considering that the implications in other energy domains are beyond the purview of this document, the model assumes that $\overline{P_m}$ and $\overline{P_n}$ remain invariant throughout the scheduling horizon.

As opposed to the initial formulation, (3.11-3.26) does not include any non-linear constraint. Therefore, it can be solved by linear open-source solvers at large-scale systems.

As illustrated in equation (3.1), the primary aim of the original model is to minimize the power exchange between the BTM system and the public grid. However, there are other potential objectives that could be considered. Two common objectives are the reduction of energy costs associated with power exchanges and the minimization of deviations from a pre-established power exchange schedule. These objectives could be incorporated into the model with minor alterations to the objective function formulations. For example, with κ_{ti}^t and κ_{te}^t being the time-dependent price of electricity and feed-in tariff respectively, the energy cost minimization can be modelled as follows:

$$\min \sum_{t=1}^{T} \left(\kappa_{ti}^t P_{ti}^t + \kappa_{te}^t P_{te}^t \right) \tag{3.30}$$

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4. Flexibility Aggregation in Front-of-the-Meter

In the default operational mode of EV chargers aggregated BTM by an energy consumer or prosumer, such as a CPO, parking lot operator, or MG operator, the controlling entity often utilizes V2X flexibility to support its priorities and objectives. As outlined in FLOW's D1.3 “Potential: Barriers & Services of Vehicle-to-Grid”, EVs can support energy autonomy and profit goals of the operators via management of V1G/V2G services for backup power provision during power outages in the public grid, increasing DER self-consumption, and energy arbitrage [9]. Yet, the impact of chargers aggregated at distinct BTM units couple beyond their meters as they often share the same grid infrastructure, creating an intricate web of dependencies and opportunities. When coordinated, the collective behavior can significantly improve the stability of the energy grid, facilitate optimized utilization of renewable energy sources, enhance the energy supply potential to EVs, and improve EV users’ satisfaction with the charging services.

This chapter delves into two specific FTM flexibility clustering strategies that offer valuable benefits to coordinated energy management. The first strategy (elaborated in Section 4.2.1) focuses on dynamic capacity sharing among BTM units, especially relevant when grid infrastructure constraints limit aggregate system consumption. In such scenarios, separate BTM units communicate in RT, negotiating how to effectively share available capacity to ensure uninterrupted service. These negotiations can leverage capacity demand calculation algorithms introduced in the BTM clustering chapter, enabling efficient utilization of resources. The second strategy (introduced in Section 4.2.2) centers on the optimized allocation of EVs to specific BTM units within the clustered system. This becomes particularly pertinent when different BTM units feature distinct types of non-flexible loads or DERs), resulting in diverse desired power consumption profiles. By strategically assigning EVs based on factors such as parking duration, energy volume requirements, and willingness to engage in V2X power transfer, it is possible to align charging demands optimally with consumption constraints, further enhancing the overall coordination and aggregation of flexibility resources.

This chapter is organized as follows. It begins by delving into the key players in this domain, providing the readers with insights into the roles of stakeholders in different flexibility clustering strategies. Then it explains two strategies (i.e., Dynamic Capacity Sharing and Optimized Allocation of EVs to Charging Locations) by presenting the reference architectures and system use cases for their implementation and formally describing the decision algorithms underlying these strategies.

4.1. Stakeholders

4.1.1. Distribution System Operator

As an entity responsible for or operating, maintaining, and managing the electricity distribution network within a specific geographic area, the usual practice for DSOs involves analyzing the viability of available capacity and connection requirements, and if necessary, the network adaptations or expansions required, to accommodate new consumers or generators.. This expansion typically includes installing equipment such as transformers, cables, and circuit breakers. However, with the advent of DER, the landscape has significantly evolved, and DSOs now are facing a challenge in managing a complex system characterized by low inertia, high dynamics, and bidirectional power flows within their operational areas. The uncontrolled charging of EVs exacerbates these challenges, leading

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to higher peaks, voltage fluctuations, and three-phase imbalances in the network. Therefore, DSOs must strategically shift their focus from solely expanding physical grid infrastructure to implementing more sophisticated grid operation and management strategies.

In the context of FTM flexibility clustering, the DSO can play a dual role in supporting cooperation. Firstly, it acts as a validator for the flexible power consumption targets of all EAs, each operating a particular BTM system. In the process of dynamic capacity sharing among EAs, the DSO verifies whether the agreed consumption profiles adhere to grid constraints, ensuring grid stability and reliability. Secondly, the DSO can offer services that facilitate flexibility clustering within its platform. For instance, it can host the charging site selection service, which identifies the optimal supply-demand match in a system comprising multiple BTM nodes. Additionally, the DSO platform can serve as a trusted marketplace for capacity negotiations between BTM consumers, enhancing the overall coordination and aggregation of flexibility resources.

To fulfill the relevant roles of FTM flexibility clustering, the DSO's technical platform should meet three requirements. First and foremost, the platform should exhibit a modular architecture that allows for the integration of a variable number of aggregators (BTM operators) and accommodates the inclusion of new ones over time. This modularity ensures adaptability and scalability as the ecosystem evolves. Furthermore, the platform should possess the flexibility to support the development of new functionalities. It should enable the creation of novel services by integrating new components or leveraging existing functions. This adaptability encourages continuous improvement and innovation within the platform. In addition, the DSO platform must handle asynchronous and synchronous communication. Certain tasks, such as requesting capacity demand and bidding capacity in a capacity sharing scenario, may necessitate asynchronous communication, where messages can be processed independently as they arrive. On the other hand, for tasks like implementing a charging site selection strategy, a more synchronous communication approach may be preferable, ensuring timely and coordinated actions.

One of the platforms that can offer the required characteristics (i.e., modularity, adaptability, supporting alternative modes of communication) is the SOGNO platform. This platform was firstly developed as part of the Horizon 2020 project SOGNO [10]. Then, its open-source code was ported to Linux Energy Foundation [11]. SOGNO platform played the role of a DSO Technical Platform in the Horizon 2020 project, Platone [12], which produced a comprehensive framework, comprising a layered set of platforms designed to cater to the requirements of system operators, aggregators, and end-users in a Blockchain based infrastructure. SOGNO has a strong reliance on a micro-service architecture. This architectural approach offers the advantages of swift adaptation, independent development, and separate deployment of components. This isolation of services aids in maintenance efforts and helps prevent the occurrence of cascading failures between different components. Containerization using Docker [13] containers is mandated for all micro-services within the platform, as it facilitates seamless deployment on a Kubernetes cluster [14]. One of its pivotal components is the Databus, realized through a Message Broker, enables all services to publish and subscribe for data exchange. This data interchange can occur internally between micro-services or externally with field devices, other platforms, or systems [15]. However, SOGNO implements also request/response communication mechanism via its RESTful APIs [16].

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Due to the above-mentioned reasons, SOGNO was the ideal environment to host the services related to the FTM flexibility clustering of V2X-flexibilities. Throughout Task 4.5 in WP4, a service prototype for the charging site selection strategy was developed.

4.1.2. Aggregators

In modern energy systems, Energy Aggregators (EAs) access the controllable resources of numerous small-scale consumers to create a more substantial flexible capacity. Different aggregation architectures can be employed in the context of FTM flexibility clustering, spanning from centralized to decentralized models. The centralistic approach involves representing all BTM units under a single EA. In the hierarchical approach, multiple EAs represent individual or multiple BTM units at a lower level, with a coordinating EA acting as the aggregator of these lower-level EAs. The distributed approach features multiple EAs, each representing single or multiple BTM units independently. This document adopts a highly decentralized architecture, where each BTM unit's DERs are collectively represented by a single EA, resulting in as many EAs as there are BTM units. In this configuration, each EA serves as a vital interface, facilitating cooperation between DSOs and the DERs within BTM units, enabling the cooperative control of V2X-capable systems and other flexible DERs, thus enhancing overall distributed energy resource management.

To fulfill their functions effectively, each EA employs computer-aided tools known as Energy Management Systems (EMS) for monitoring and controlling DERs, both BTM and FTM [17]. These sophisticated systems enable in-depth analysis of load-generation behaviors, encompassing EV charging related aspects such as charging frequency, duration, and preferred charging locations. In the context of FTM flexibility clustering, the EMSs of EAs play pivotal roles in enabling two essential coordination strategies.

The first strategy, dynamic capacity sharing between BTM units, relies on EAs to meticulously calculate the capacity demand of each BTM unit. In this case, EAs consider a comprehensive spectrum of factors, incorporating all associated DERs and non-flexible loads within the BTM unit. Subsequently, EAs engage in seamless communication with other EAs to either request additional capacity or distribute their excess capacity as needed. This dynamic process ensures the optimization of capacity utilization within the clustered system, promoting enhanced grid stability and efficient resource management.

In the implementation of the second strategy, optimized allocation of EVs to specific BTM charging units within the clustered system, EAs take on the responsibility of closely monitoring the availability of charging units within their purview. When the site selection service is activated for an incoming EV, these EAs swiftly engage by bidding their charging offers. This RT interaction aligns the unique characteristics and requirements of each EV with the available charging infrastructure, ensuring that EVs are intelligently directed to the most suitable BTM charging units. Consequently, the cooperative objectives of the FTM cluster are harmonized with the diverse needs and preferences of EV users, ultimately enhancing the overall satisfaction and efficiency of the charging services.

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4.1.3. Electromobility Service Provider

Energy Mobility Service Providers (EMSPs) are entities that directly engage with EV drivers to cater to their individualized charging needs, both in private and public settings. These specialized providers offer a range of services, facilitated through mobile applications, encompassing payment processing and customer assistance. One of the EMSP services of paramount significance, particularly in ecosystems with multiple BTM units, is EV roaming. In scenarios where drivers seek to charge their EVs at locations other than their habitual destination charging points, EMSPs play a pivotal role by assisting them in several key aspects. Firstly, EMSPs aid drivers in identifying accessible charging spots situated within public premises. Secondly, they facilitate seamless communication of the drivers' specific charging preferences. Lastly, EMSPs streamline the payment process for the rendered charging services. Importantly, through the provision of these services, particularly the ability to identify available charging locations and accommodate driver preferences, EMSPs wield the capacity to influence both the timing and geographic distribution of EV charging activities. Consequently, these actions wield the potential to impact the load profile of distribution grids, thereby highlighting the substantial role played by EMSPs in shaping the energy landscape.

The EMSP actively engages in the optimized EV allocation strategy, serving as the intermediary link between EV drivers and the DSO. Within its comprehensive database, the EMSP stores pertinent information, including details concerning EV battery capacity and compatible charging modes. When an EV driver approaches or intends to visit an area offering multiple BTM charging alternatives, the EMSP combines this static data with the specific requests obtained directly from the driver. These specific insights pertain to the driver's charging preferences, encompassing elements like the intended destination, maximum permissible walking distance, estimated parking duration, V2G allowance. The EMSP then transmits this consolidated dataset to the DSO, which subsequently leverages this information to facilitate the charging site selection service and eventually, informs the driver when the service determines the best available charging offer.

4.2. Coordination Strategies

4.2.1. Strategy 1: Dynamic Capacity Sharing

Dynamic capacity sharing addresses the challenges arising when the loading of multiple BTM entities affect the same local grid part. The essence of this strategy lies in its adaptability, enabling the efficient allocation and sharing of electrical capacity among these entities to optimize grid utilization and maintain grid stability. Imagine two separate BTM units, both drawing power from a shared transformer with a rated capacity of 500 kVA. The critical aspect here is that at different times, this 500 kVA resource can be shared and distributed in varying proportions, depending on the evolving demands of each unit. Dynamic capacity sharing offers a dynamic solution to this intricate puzzle, enabling RT adjustment of capacity allocation to cater to the specific needs and priorities of each BTM entity while ensuring that grid constraints are not breached.

This FTM flexibility clustering strategy introduces a new layer of complexity and requires careful consideration of conditions to ensure that the benefits outweigh the potential risks. One of the foundational steps in implementing dynamic capacity sharing is accurately calculating the capacity demand of each BTM entity.

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For efficient capacity sharing between multiple BTM entities, ensuring data security, real-time communication, and seamless decision-making is paramount. This can be enabled by a sufficient digital architecture. The subsequent sections explore both decision making and architectural components in greater detail, shedding light on the methodologies and considerations that underpin the successful deployment of dynamic capacity sharing as a key element in BTM flexibility clustering.

4.2.1.1. Concept Architecture

The concept architecture assigns the tasks required for the implementation of the dynamic capacity sharing to two types of virtual entities. The FTM coordinator is responsible for identification of the aggregate capacity constraint -which can be shared between multiple BTM units in alternative distributions— of the FTM cluster and validating the specific instances of capacity sharing after two or more BTM units decide to use the given capacity in a certain way. In the clustering environment, there exist multiple BTM units. These BTM employ EMSs to track the status of the assets under their control, predict the future loading and generation, calculate their capacity demand, and if relevant, to share capacity sharing duration.

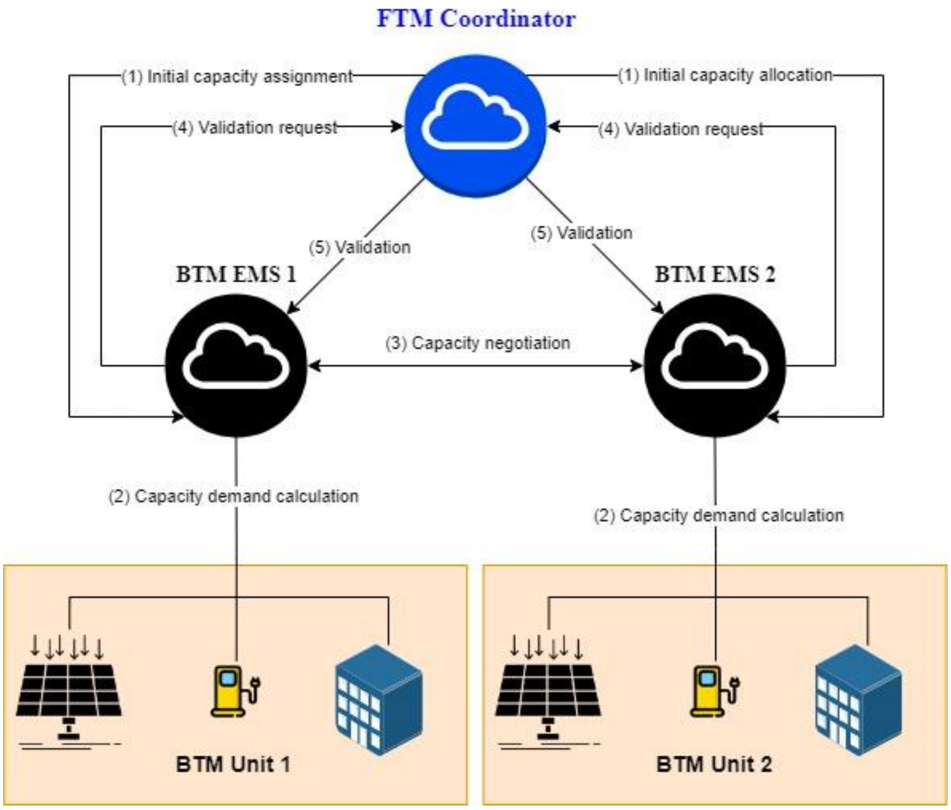

Figure 2. System architecture for dynamic capacity sharing between BTM units.

Figure 2 illustrates the workflow to implement the intended concept. In this workflow, the FTM Coordinator determines the available total capacity for each BTM units in the clustering environment. The underlying process and timeline are not within the scope of this document. For the sake of generality, this document presumes that the FTM coordinator determines the capacity for a specific capacity sharing period $[k, k + T^R)$ where k indicates the start of the period and T^R the duration. The capacity that the FTM coordinator assigns to a specific BTM unit denoted by c for the $[k, k + T^R)$

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period is represented by $\Phi_c(k)$ in the following. The process starts with the FTM coordinator sending $\Phi_c(k)$ to the BTM EMSs. Then, based on the status of the devices, charging commitments and predicted load-generation between $[k, k+T^R)$, each BTM unit determines its minimum capacity demand, $\overline{p_c}(k)$, for the same period. The BTM units that need more capacity than the one allocated to them at the first place, that is $\overline{p_c}(k) > \Phi_c(k)$, are allowed to access to other BTM operators to request using their capacities to cover their deficit, $\delta_c^-(k) = \overline{p_c}(k) - \Phi_c(k)$. After an agreement between two BTM operators, the outcome is shared with the FTM coordinator for validation. If the new way that the BTM operators suggest sharing the given capacity is feasible, then the FTM coordinator validates the sharing and informs the BTM EMSs.

4.2.1.2. Role Allocation

The activities carried out within the Platone project have generated the reference architecture and ground knowledge required for orchestrating capacity sharing between multiple BTM units in a multi-platform environment.

In particular, the German Demo Architecture [18] provides a reference for implementation of the concepts like the one defined here. In Use Case 2, all energy assets —including local generation, demand and storage—below the secondary substation is controlled by an EMS owned by the local energy community. The DSO calculates a target value for the secondary substations' power exchange with the shared MV grid and sends these target values to the local energy community's EMS via the DSO technical platform. This EMS forecasts the local generation and demand to optimize the controlled assets behaviour in a way to converge the target value set by the DSO; the DSO is not interested in how individual assets withdraw and inject power provided that the respective secondary substation measures the targeted value. In this picture, the secondary substation is identical to the meter separating a particular consumer premise from the public system. The entity representing the BTM unit in this setup is equivalent to an EA, which monitors and controls the consumption-generation below a secondary substation.

The Platone solution comprises a layered set of platforms designed to cater to the functional and non-functional requirements of similar use cases. These platforms are collectively referred to as the Platone Open Framework. A key component within this framework is the Platone Market Platform, which operates on a blockchain-based infrastructure. This platform facilitates the management of flexibility requests spanning wide geographical areas, accommodating local flexibility requests from DSOs. All market operations are recorded and certified within the blockchain service layer. During the implementation of the concept defined in Section 4.2.1.1, such a layer records all the vertical (between DSO and EAs) and horizontal information exchanges (between EAs). Thus, the blockchain service layer enhances transparency, security, and trust among all participants.

4.2.1.3. Short Term Capacity Demand Calculation

This section outlines the procedure through which individual EAs -each representing a BTM unit in the FTM clustering ecosystem- determine their capacity demands before initiating negotiations with other EAs for capacity sharing. In this regard, each EA's EMS solves an optimization problem aimed at identifying the minimum required capacity, denoted as $\overline{p_c}$, for ensuring the timely completion of scheduled charging services. The capacity demand calculation for the estimated capacity sharing duration, T^R, is formally represented as follows:

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$$\min \overline{p_c} \qquad 4.1$$

$$\sum_{\forall v \in V_c(t)} p_v(t) + \sum_{\forall a \in A_c} p_a(t) \leq \overline{p_c} \qquad 4.2$$

$$s_v^*(k + T^R) \leq s_v(k + T^R) \qquad 4.3$$

$$s_v(t + \Delta t) = s_v(t) + \frac{p_v(t) \cdot \Delta t}{C_v} \qquad 4.4$$

$$\underline{p_a(t)} \leq p_a(t) \leq \overline{p_a(t)} \qquad 4.5$$

To improve readability, a summary of the notation used within this model is provided in the following:

k	Time indicator of the start of the capacity sharing duration
T^R	Parameter. Capacity sharing duration. [seconds]
t, Δt	A particular time step within the capacity sharing duration $t \in (k, k + T^R)$ and time sampling size.
A_c, a	Set of flexible asset in BTM system *c* and their identifiers.
$V_c(t)$, v	Set of EVs available in BTM system *c* at *t* and their identifiers.
C_v	Parameter. Energy capacity of the EV battery. [kWh]
$\underline{p_a(t)}$, $\overline{p_a(t)}$	Parameter. Lower and upper bound of the aggregate power consumption of other (non-EV) flexible assets at *t*. [kW]
$s_v(k + T^R)$	Variable. SOC to be achieved by *v* at $k + T^R$. [%]
$p_v(t)$	Variable. Net power consumed by *v* at *t* . [kW]
$\overline{p_c}$	Variable. Minimum capacity needed by the BTM unit within the sharging duration. [kW]

In this optimization problem, the control variables pertain to the net power consumption of energy assets aggregated BTM, comprising EVs and other flexible and non-flexible components. In the optimization model the charging/discharging powers of the EVs are represented by variables, $p_v(t)$ and the net power consumption of other assets by a respective $p_a(t)$. The variable set includes one element for each EV connected in the BTM system for each time step within the capacity sharing period, denoted as $[k, k + T^R)$. $V_c(t)$ is the set of EVs connected in BTM at t and V_a the set of other energy assets comprising both flexible and non-flexible ones.

The objective function (4.1) minimizes the net peak power consumption of the BTM. Here, it is assumed that T^R is a predefined value within the given FTM cooperation model. The inequality (4.2) represents the linear expression of peak power consumption. The left-hand side of the inequality expresses the aggregate net consumption of the BTM unit. The model incorporates the constraint (4.3) to ensure that the SOC levels specified by reference schedules, which target a given BTM objective such as quickest schedule to reach the targeted SOC or the one tailored to cost-minimization goals of

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the BTM operator. The constraint (4.4) expresses the SOC increase over a particular control interval, lasting for Δt. In these equations, $s_v(t)$ is a dependent variable indicating the SOC at t and C_v the battery capacity. For the sake of generality, the power consumption constraints of the assets apart from the EVs, the limits of the net consumption of each asset a is expressed with a range specified by lower and upper bounds, $\underline{p_a(t)}$ and $\overline{p_a(t)}$, in constraint (4.5). The optimization model presented in Section 3 provides the details for explicit definition of (4.5).

4.2.1.4. Capacity Sharing

Each aggregator's EMS assesses its minimum capacity demand, $\overline{p_c}(k)$, calculated using equations (4.1) to (4.5), and compares it with the initial capacity assignment, denoted as $\Phi_c(k)$, sent by the DSO. In the scenario where $\overline{p_c}(k) < \Phi_c(k)$, the aggregator has the capability to share its excess capacity, denoted as $\delta_c^+(k)$, which is determined as $\delta_c^+(k) = \Phi_c(k) - \overline{p_c}(k)$, with other aggregators. Conversely, in situations where $\overline{p_c}(k) > \Phi_c(k)$, the aggregator seeks to address its capacity deficit, denoted as $\delta_c^-(k)$, which is calculated as $\delta_c^-(k) = \overline{p_c}(k) - \Phi_c(k)$, by utilizing the surplus capacity of another aggregator.

In the context of capacity sharing negotiations, the aggregator EMSs communicate in peer-to-peer setting. Aggregators possessing surplus capacity receive capacity requests from aggregators representing systems with capacity deficits. For instance, if aggregator c_1 has a surplus capacity of $\delta_{c_1}^+(k)$ and receives a request from aggregator c_2, which has a deficit of $\delta_{c_2}^-(k)$, c_1 may permit c_2 to utilize its capacity up to $\delta_{c_1}^+(k)$. If this arrangement is approved by the DSO, then c_2 can access $\phi_{c_2}(k) + \delta_{c_1}^+(k)$ capacity instead of just $\phi_{c_2}(k)$. In cases where the additional capacity provided by c_1 is insufficient to cover the deficit of c_2, c_2 can explore other agreements with the remaining aggregators. While aggregators are theoretically permitted to continue making requests until they eliminate all their capacity deficits, such negotiations are subject to time constraints.

Capacity-sharing agreements are made with a specific future timeframe in mind. However, uncertainties surrounding future events introduce risks for aggregators providing capacity to others. For example, if new EVs connect to the chargers controlled by the aggregator that agreed to share its surplus with another aggregator, the "capacity provider aggregator" may experience a reduction in its supply potential. Similarly, the sudden disconnection of an EV can lower the actual capacity demand of a capacity consumer. This document does not delve into strategies for quantifying the risk and benefit of capacity sharing. However, for the sake of applicability, the capacity agreements must be bound with optimally designed incentives resilient to uncertainties and align with the interests of all parties involved. In a suitable business model, aggregator c_2 compensates aggregator c_1 with an amount that (1) covers potential losses incurred by c_1 due to relinquishing capacity and (2) benefits c_2 by increasing its power consumption limits. Additionally, within the overall business model, compensation must also be provided for the services rendered by the DSO.

4.2.2. Strategy 2: Optimized Allocation of EVs to Charging Locations

Each driver's expectation from the charging service is unique, with varying requirements regarding the targeted SOC, anticipated parking duration, and willingness to provide V2X energy. However, provided they remain sufficiently close to their intended destinations and achieve their desired SOC within a specific timeframe, some EV drivers would possess the flexibility to choose different locations for

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charging their cars. This spatial dimension can serve as a valuable resource when aggregating the V2X-flexibilities of closely situated BTM systems. This approach becomes particularly advantageous when different BTM systems have diverse preferences/constraints regarding their power consumption profiles. By strategically directing EVs to optimal charging locations, it is possible to find the best demand-supply matches, and efficiently balance energy consumption, thus enhancing overall system performance.

The reasons for varying power consumption profiles among neighboring BTM systems can stem from a range of factors. One such factor could be the nature of their non-flexible loads. Suppose two different commercial entities own two BTM systems, where one's power consumption peaks before noon, while the other's peak occurs after noon. In case two BTM entities are clustered in the same FTM aggregation system, EVs can be allocated strategically to align with peak-shaving objectives. For instance, EVs arriving before noon with urgent charging demands and no V2X willingness could be directed to the second BTM system, helping reduce its net consumption during peak hours. Conversely, EVs arriving before noon with high SOC levels in their batteries and a willingness to supply power to the grid or the premises could be directed to the first BTM system, aiding in reducing overall consumption in that area.

The diversity in desired power consumption profiles among neighboring BTM systems can arise from the specific DERs incorporated within each system. For instance, one BTM system may be equipped with PV panels that primarily generate power during daylight hours, while another may rely on a CHP unit that can operate continuously. These distinct DER configurations can lead to varying patterns of energy production. For instance, during daylight hours when the PV-equipped BTM system is generating surplus electricity, it can be advantageous to direct EVs to that location for charging. Meanwhile, during periods when the CHP-based BTM system is producing heat, the grid FTM can benefit from EV charging, which reduces the power exported back to the grid. By orchestrating the charging and discharging of EVs based on the specific DER capabilities and operational characteristics of each BTM system, it is possible to maximize the utilization of renewable energy, enhance grid stability, and optimize the overall energy landscape.

4.2.2.1. Concept Architecture

The examples provided above highlight the benefits of considering the complementary nature of the temporality imposed by non-flexible loads and DERs in different BTM systems. However, “What is the best location where the EV charging or discharging can best complement the existing energy ecosystem?” is a complex question. If all relevant constraints –from all clustered BTM systems as presented in models described in Section 3.3.2-- were incorporated into a single decision problem, this would create a computationally intensive task. Attempting to solve such a problem centrally for all clustered BTM systems may face limitations in terms of scalability and the risk of creating a single point of failure within the coordination framework. However, it is possible to reduce the size of the central problem if the temporality of the local constraints is depicted implicitly through time-dependent pricing for EV charging. By introducing dynamic pricing mechanisms that vary based on both the time and location of EV charging, it is possible to incentivize EVs to naturally gravitate towards the locations and times that align with the specific requirements and constraints of each BTM system.

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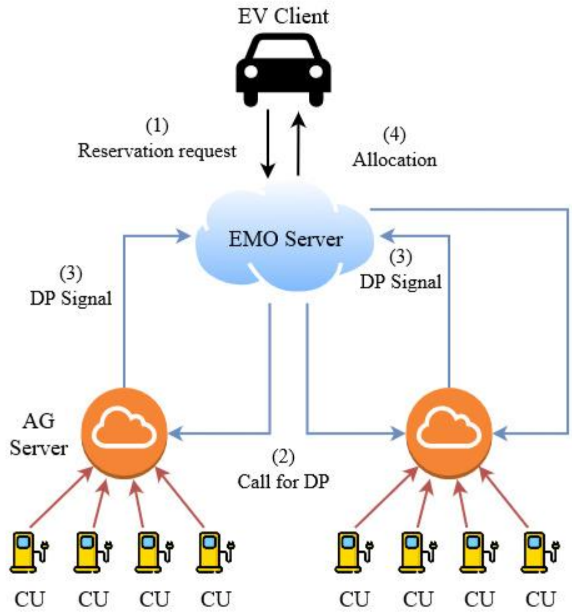

Figure 3. System architecture for the charging site selection based on dynamic pricing [7].

A recent publication, [7], introduces an EV charging management concept based on price-oriented routing of EVs. This paper defines a virtual entity, referred to as an *electro-mobility operator (EMO)* that is authorized to collect price signals from multiple aggregators and solve an optimization problem, which finds the offer with the minimum charging cost for the incoming EVs. The authors of [7] define a business use case (BUC), as depicted in Figure 3. In this BUC, first, the EV user sends a reservation request to the EMO server. Then, the EMO calls aggregators (AGs in Figure 3) having available charging units (CUs) for dynamic pricing (DP). Next, the aggregators calculate their time-dependent price signals (i.e., DP signals). Finally, the EMO reserves a charger for the EV, informs the EV user about the reservation, and sends the reference schedule to the reserved CU.

4.2.2.2. Role Allocation

In FTM flexibility clustering, the tasks determined by [7] can be distributed to the stakeholders in different ways. However, considering the existing roles and capabilities of the stakeholders, this document suggests a specific approach. In this approach, the DSO takes the role of the EMO; the DSO platform provides the charging site selection function as a service via an API where the EMSPs can submit their service requests. The DSO platform can communicate with external aggregators (both energy and data aggregators) to request their inputs for the service. In this ecosystem, an external service provider functions as the intelligent transport system (ITS). This service provider, incorporating respective maps and forecasting tools, estimates the vehicles' arrival time to reach each specific candidate location and the amount of energy it will consume on the route in response to the request of the DSO platform. After receiving inputs from both EMSP and ITS, the DSO platform requests charging offers from the BTM systems in the search space. Here, a specific energy aggregator (EA) represents each BTM system and sends its charging offers upon the DSO's request, fulfilling the AG server's tasks in Figure 3.

The charging site selection service starts when the EMSP sends a service request to the service platform (i.e., DSO platform in the suggested approach) for a particular vehicle. Let us represent this vehicle by v. The request includes a set of parameters that define the constraints for optimizing the

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charging or discharging of EVs. The first subset of the parameters includes the vehicle-specific parameters such as energy capacity (C_v), maximum charge (P_v^+), and discharge power (P_v^-) of the battery, and the vehicle's characteristic energy consumption in different road conditions. Another subset indicates the driver's charging demand parameters such as target SOC (s_v^T), V2G allowance (δ_v^T), and estimate departure time (D_v^T). The third subset indicates the drive start conditions (time and initial SOC) and search space specifications (target destination and maximum walking distance). All these parameters jointly indicate where the driver wants to charge and how much flexibility they will provide to the BTM operators when they bring their vehicles to the respective charging locations.

The execution of the charging site selection service follows a three-stage process. In the first stage, the service platform identifies the candidate locations that fall into the search space of the driver with the help of the ITS. The ITS is an external DA unit, which is assumed to produce location-dependent arrival SOC ($\widetilde{S_{c,v}}$) and arrival time ($\widetilde{A_{c,v}}$) estimations for the incoming vehicle, in response to the request of the service platform. Here c represents a particular BTM system within the search space of v. At this level, the service platform communicates the vehicle's drive start parameters (i.e., initial SOC and drive start time) it received from the EMSP. After receiving inputs from the ITS, the service platform requests charging offers from the EAs. The EAs determine the available chargers ($\upsilon_{c,v}$) and available energy ($E_{c,v}$) that can be allocated to v if it is directed to the specific location represented by c. Besides, the EAs associate a price signal –with presumably higher values for the periods when they prefer to reduce the aggregate load of the BTM system. The third stage focuses on identifying "sufficient" offers. This stage considers the offer "sufficient" when $E_{c,v}$ is equal to or exceeds the specific amount requested by the vehicle (i.e., vehicle reaching s_v^T after charging at v. In this evaluation, the location-dependent arrival time and SOC estimations provided by the ITS help incorporate the impact of the energy consumed on the route toward the charging location. Consequently, the third filters out offers that do not meet the vehicle's energy requirements, thus narrowing down the options for the subsequent stage. Finally, the fourth stage delves deeper into the optimized site selection problem.

4.2.2.3. Optimized Offer Selection

Given the various potential charging locations and their associated arrival times, the optimization horizon spans from the earliest predicted arrival time ($\underline{A_v}$) to the latest projected departure time ($\overline{D_v}$). The optimization horizon is discretized into time steps, indexed by t. For instance, one of the key optimization outputs, $p_v^+(t)$, represents the planned charge power during a particular time step $[t+\Delta t)$. Here, t and Δt represent the time step identifier and duration for which the charge power will be implemented.

$$\sum_{c\,\in\,C}\ \sum_{t=\widetilde{A_{c,v}}}^{\widetilde{D_{c,v}}} \omega_{c,v}^+(t)\, p_{v,c}^+(t) - \omega_{c,v}^-(t)\, p_{v,c}^-(t) \tag{4.6}$$

subject to

$$0 \le p_{v,c}^+(t) \le \rho_{c,v}^+\ z_{c,v}(t)\, x_{v,c} \tag{4.7}$$

$$0 \le p_{v,c}^-(t) \le \rho_{c,v}^-\ z_{c,v}(t)\, x_{v,c} \tag{4.8}$$

$$\sum_{c=1}^{C} x_{v,c} = 1 \tag{4.9}$$

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$$p_v^+(t) = \sum_c^C p_{v,c}^+(t) \quad 4.10$$

$$p_v^-(t) = \sum_c^C p_{v,c}^-(t) \quad 4.11$$

$$0 \le p_v^+(t) \le P_v^+ \, x_v^+(t) \quad 4.12$$

$$0 \le p_v^-(t) \le P_v^- \, x_v^-(t) \quad 4.13$$

$$x_v^+(t) + x_v^-(t) = 1 \quad 4.14$$

$$s_v(t + \Delta t) = s_v(t) + \frac{(p_v^+(t) - p_v^-(t)) \, \Delta t}{C_v} \quad 4.15$$

$$\underline{s_v} \le s_v(t) \le \overline{s_v} \quad 4.16$$

$$s_v\left(\underline{A_v}\right) = \sum_{c \in C} \widetilde{S_{c,v}} \, x_{v,c} \quad 4.17$$

$$s_v\left(\overline{D_v}\right) = s_v^T \quad 4.18$$

$$\sum_{t=A_v}^{D_v} p_v^-(t) \, \Delta t \le \delta_v^T \quad 4.19$$

To improve readability, a summary of the notation used within this model is provided in the following:

$t, \Delta t$	Time step identifiers and time sampling
C, c	Set of BTM systems and their identifiers (c $\in 1,..,C$)
V, v	EV set and identifiers *(v* $\in 1,..,V$*)*
$\widetilde{A_{c,v}}, \widetilde{D_{c,v}}$	Parameter. Estimated arrival and departurte times of *v* to the BTM unit *c*.
$\widetilde{S_{c,v}}$	Parameter. Estimated arrival SOC if *v* is instructed to *c*. [%]
$\underline{A_v}$	Parameter. Earliest arrival time of *v* to one of the BTM units in the area.
$\overline{D_v}$	Parameter. Latest departure time of *v* from one of the BTM units in the area.
C_v	Parameter. EV battery's energy capacity. [kWh]
P_v^+, P_v^-	Parameter. Maximum charge and discharge power that can be accepted by EV battery. [kW]
$\rho_{c,v}^+ \ , \rho_{c,v}^-$	Parameter. Maximum charge/discharge power that the charger offered by *c* can inject/withdraw to/from EV battery. [kW]
$\underline{s_v}, \overline{s_v}$	Parameter. Lower and upper boundary of the SOC range of the EV battery. [%]
$\omega_{c,v}^+(t), \omega_{c,v}^-(t)$	Parameter. Prices of G2V charge and V2G discharge at *c* during *t*. [Eur/kWh]

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s_v^T	Parameter. Target SOC specified by the driver of *v*. [%]
δ_v^T	Parameter. V2G allowance specified by the driver of *v*. [kWh]
$p_{v,c}^+(t)$, $p_{v,c}^-(t)$	Variable. Net charge and discharge power of *v* at *t* if it is allocated to *c*. [kW]
$p_v^+(t)$, $p_v^-(t)$	Variable. Net charge and discharge power of *v* at *t*. [kW]
$x_v^+(t)$, $x_v^-(t)$	Variable. Charging status of *v* (charge and discharge) at *t*. [Binary]

The objective function (4.6) serves as a representation of the charging and discharging processes of EVs within all potential candidate BTM systems, with dedicated variables $\mathrm{p}_{\mathrm{v,c}}^+(\mathrm{t})$ and $p_{v,c}^-(t)$ utilized to indicate and weigh the various charging schedules in conjunction with the associated price signals denoted as $\omega_{\mathrm{c,v}}^+(\mathrm{t})$ and $\omega_{c,v}^-(t)$. The constraints articulated in (4.7) and (4.8) play a pivotal role in shaping the charging and discharging activities, stipulating that $p_{v,c}^+(t)$ and $p_{v,c}^-(t)$ can assume non-zero values exclusively when vehicle v is physically present within BTM c at time t. To meet these conditions, two fundamental criteria must be satisfied. Firstly, time t should fall within the estimated parking duration of vehicle v in BTM system indicated by c. This temporal requirement is effectively conveyed by the binary parameter $z_{c,v}(t)$, which takes on a value of 1 when $\widetilde{A_{c,v}} \leq t < \widetilde{D_{c,v}}$, and assumes a value of 0 otherwise. Secondly, vehicle v must be assigned to BTM c through the optimization process, as reflected by the binary variable $x_{v,c}$. This binary variable assumes a value of 1 if vehicle v is directed to BTM system c, while taking on a value of 0 if not. The presence of a non-zero value for $x_{v,c}$ is a prerequisite for $p_{v,c}^+(t)$ and $p_{v,c}^-(t)$, ensuring that the respective charging or discharging activities are carried out. Constraint 4.9 reinforces this requirement, specifying that only one of the $x_{v,c}$ variables can assume a value of 1 at a given time, thereby ensuring the allocation of vehicle v to a single location. This allocation process ensures that only the corresponding price signals, $\omega_{c,v}^+(t)$ and $\omega_{c,v}^-(t)$, impact the overall objective function. Notably, $x_{v,c}$ is not indexed by time t, as the service does not consider multiple travels between different BTM systems once the EVs have been assigned.

Constraint (4.10) outlines the requirement for the charge power to be delivered to vehicle v during the time interval $[t, t + \Delta t)$, denoted as $p_v^+(t)$, which is the sum of variables representing charge power in particular BTM systems, $p_{v,c}^+(t)$. Given that constraint (4.9) ensures that $x_{v,c}(t)$ equals 1 for only one specific BTM c, $p_v^+(t)$ is equivalent to $p_{v,c}^+(t)$ for the cluster c to which vehicle v is allocated. Similarly, constraint (4.11) employs the same principle for the discharging scenario. In addition to the charge and discharge power ratings of the off-board charging equipment, indicated by $\rho_{c,v}^+$ and $\rho_{c,v}^-$ in (4.7) and (4.8), the on-board components of the charging system impose limitations on the power that can either be injected into or withdrawn from an EV battery. Inequalities (4.12) and (4.13) incorporate these restrictions into the optimization problem, constraining the net charging and discharging power at all time instances based on the charge (i.e., positive limit, P_v^+) and discharge (i.e., negative limit, P_v^-) power that can be accommodated by vehicle v due to the limitations of its on-board equipment. Constraint (4.14) stipulates that only charging or discharging can occur within a specific time interval t; hence, if $p_v^+(t)$ takes a non-zero value, $p_v^-(t)$ must be zero, and vice versa.

The SOC increases during the charging process and decreases during discharging, as defined by (4.15). To establish the lower and upper boundaries of the SOC within the optimization horizon, the inequality (4.16) takes into account the parameters specified by the EV driver. Constraint (4.17) highlights that

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the considered arrival SOC is dependent upon the variable $x_{v,c}$, signifying the selected charging offer. In addition, (4.18) ensures that regardless of the chosen charging location, the targeted SOC (s_v^T) must be attained by the end of the optimization horizon. The combined effect of constraints (4.17) and (4.18) inherently encourages charging at sites that can be reached without consuming additional energy. Opting to charge at more distant locations would entail higher energy consumption during the journey, resulting in an increased demand for net energy supply. Exceptions may arise in rare scenarios where potential cost savings from charging outweigh the extra expenses incurred due to heightened charging demand. Nevertheless, such cases are unusual and do not reflect typical behavior, as dictated by the constraint. Lastly, inequality constraint (4.19) restricts the cumulative V2G discharge total, following the V2G allowance denoted as δ_v^T.

The optimization algorithm generates two key outcomes: the chosen charging location denoted as $\gamma_v = c$ for c where $x_{v,c}$=1, and the resulting charging schedule, $p_v = p_v^+ - p_v^-$. However, the charging schedule, p_v, also provides information about the final SOC to be reached by the end of the planned parking duration and the total V2G supply over this timeframe. Another important aspect influenced by the selected schedule is the value of the objective function. In essence, this represents the lowest charging cost that the driver of vehicle v would face when charging their vehicle's battery to the desired SOC, considering the available charging offers. However, based on the premise that price signals reflect the preferred consumption profiles of the BTM entities, the cost-optimal choice of location and charging schedule aligns with the most suitable behavior for the cooperative objectives of the FTM cluster.

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5. Flexibility Aggregation on UCD Campus Grid

5.1. Motivation

This chapter serves as a practical demonstration of the effectiveness of one of the FTM flexibility aggregation strategies: optimized allocation of EVs to specific locations (see Section 4.2.2). The selected scenario, the campus network of UCD, offers a well-suited environment for this study due to several compelling factors.

Physical Layout: The UCD campus network has a physical layout that aligns perfectly with the research objectives. The UCD MV distribution network accommodates 30 MV buses on four radial feeders as depicted in Figure 4. It features several parking lots distributed across the campus, each serving as a potential charging location. Most EV drivers typically park their vehicles and then walk to various faculties and destinations within the campus. Provided the allocation does not lead drivers to disproportionately distant locations, it is reasonable to anticipate their cooperation. This high level of potential acceptance and adaptability among drivers is not unique to the UCD campus; it mirrors the behavior commonly observed in university settings, making this scenario broadly representative.

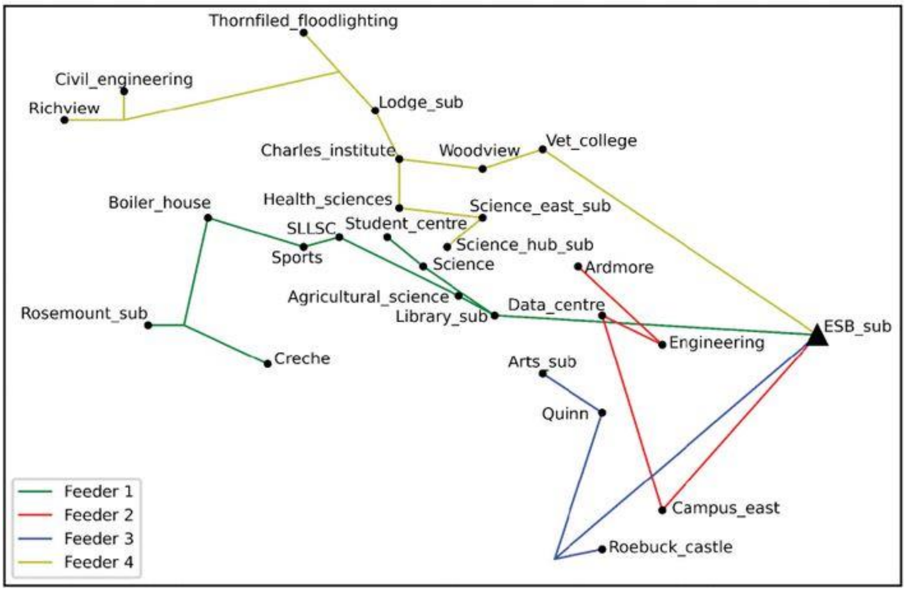

Figure 4. UCD Campus Network [19].

Grid Capacity Challenges: The UCD campus also presents an opportunity to address an anticipated challenge related to grid capacity. Previous research [19] indicated that the campus's electrical grid may encounter capacity constraints with the projected increase in EV adoption. To be specific, when the EV penetration rate increases to 50% level (with every second parking lot being occupied by EVs demanding charging in the campus infrastructure), the main cable in *Feeder 4* –the one between *Vet_college* and *ESB_sub* in Figure 4— is expected to reach the limit of overloading. At this penetration rate, the MV/LV transformers fed by *Feeder 4* will experience distinct peak loading rates. The transformers labeled as *richview_tx1* and *civil_engineering_tx1* are frequently observed to be operating beyond their designated capacity, indicating a substantial overload situation. This increased strain on their capacity is likely attributed to the heightened demand for EV charging concentrated in these areas. In contrast, the transformer labeled as *vet_college_TX2* despite being located on the same

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feeder line, remains significantly underused even under comparable conditions. This potential challenge underscores an opportunity to test and validate optimization strategies capable of alleviating grid stress by redistributing the load across different parts of the grid. By addressing these challenges proactively, the proposed flexibility aggregation strategy can offer practical solutions to an emerging issue, contributing to the sustainable integration of EVs into campus environments.

Intelligent Reservation System: Additionally, the UCD campus serves as a testbed for an intelligent reservation system designed to manage shared EV charging facilities. This program aims to enhance the utilization of existing chargers, effectively increasing the supply potential of the infrastructure without requiring extensive capacity extensions. This objective aligns seamlessly with the core promise of exploiting the spatial dimension of EV flexibility: maximizing the service potential of identical systems. Our case study explores the implementation and impact of this intelligent reservation system within the UCD campus, shedding light on its effectiveness and potential scalability for similar settings.

It is important to note that this case study applies the optimized allocation strategy in a private network, which constitutes a large BTM system. This may appear to conflict with the terminology established in previous chapters since optimized allocation was categorized as an FTM aggregation strategy in Chapter 4. From the perspective of the specific objectives targeted by this document, such as alleviating grid challenges, increasing supply potential, and improving EV users' experience, the BTM/FTM categorization becomes less relevant. The applicability of optimized allocation is not strictly dependent on the peculiarities at these aggregation levels. The layout of the targeted test network is more important. For instance, the parking lots of each faculty, supplied by a specific MV/LV transformer in the network, are local aggregation units equivalent to BTM units within a multi-level aggregation system.

In summary, the UCD campus case study offers a practical and relevant environment to examine the optimized allocation of EVs as a flexibility aggregation strategy, which addresses the adaptability of EV drivers to dynamic charging site allocation, potential grid capacity challenges, and the impact of intelligent reservation systems, all contributing to the broader goals of sustainable and efficient EV integration.

5.2. Test Scenario

The test scenarios assume that the campus network comprises multiple BTM systems, where the MV/LV transformers represent the metering points. Each BTM system includes a charging site alongside the fixed electrical consumers (e.g., faculty building). An EA is responsible for keeping the BTM’s aggregate net behavior within the limits allowed by the MV/LV transformers. This EA monitors all EVSEs in its control area as well as predicting the consumption of the included buildings. Based on the existing charging commitments and predicted non-flexible load, it calculates dynamic price signals.

In the baseline behavior, EVs follow a random selection process among the available charging locations without any preemptive communication with the charging infrastructure. They simply connect to one of the chargers at the randomly chosen location. The chargers are assumed to be capable of detecting vehicle model –and thus the battery capacity etc.-- upon connection and providing an interface so that the drivers can specify their estimated departure time and the desired SOC for charging session. Following this assumption, the EA of the respective area determines the price signal and optimizes the charging profile according to this signal.

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The case study compares the baseline behavior with so-called optimized behavior where, the campus estate management --which also acts as the DSO of the campus--, provides the optimized EV allocation service. It collects the offers from the EAs when an EMSP sends a request for a particular EV as described in Section 4.2.2.2.

This case study envisions a homogeneous infrastructure within each BTM unit (below MV/LV transformers in the network) featuring V1G chargers with 11 kW power rating and a 95% conversion efficiency. This configuration aligns with the original assumptions outlined in [19]. The uniformity in this scenario simplifies the assessment of the direct consequences of actively distributing incoming EVs among various accessible charging locations. As mentioned in Section 5.1, this scenario considers 50% penetration. Table 1 lists the scenario parameters related to the charging infrastructure in the 50% penetration scenario alongside the power capacities of the MV/LV transformers supplying power to specific charging sites. It is important to note that in the baseline behavior (i.e., when the EVs' allocation are not optimized), this is also the number of EVs using the respective charging location per day. However, the distribution of the given 478 EVs into three locations change under the optimized behavior.

Table 1. Charging infrastructure on Feeder 4 of UCD network at 50% EV penetration scenario.

Location	Transformer capacity (kVA)	Number of parking space	Number of EVSEs (EVs in baseline operation)
vet_college	1600	339	170
richview	200	133	66
civil_engineering	1000	484	242
Total		952	478

In the simulated scenario, EVs approaching the campus from the south send site selection requests near Costcutter, specifying the UCD Student Centre as their destination (see Figure 1). Depending on their assigned charging location (Richview Library, Civil Engineering Faculty, or Veterinary School), they enter the campus through different gates, with estimated distances of 2.2 to 2.4 kilometers and driving times ranging from 5 to 10 minutes. Walking durations from these charging sites to various campus destinations vary between 7 to 13 minutes. This controlled scenario minimizes external factors like traffic, allowing a more focused evaluation of the university's power system impact.

In the case study, the load measurements recorded in 2019 for the transformers were presumed to be perfect predictions for the day-ahead load forecasts of the non-EV load. These recorded values were subtracted from the nominal ratings of the transformers, yielding the available capacity for EV charging in the respective areas. In the simulations, the same parameters, representing the transformer loads observed on specific days in 2019, were considered as the cumulative non-EV load. For instance, if the net load measured by the transformer *civil_engineering_tx1* between 08:00-08:15 on 5th April 2019 was 116 kVA, and the transformer's power rating stood at 1000 kVA, the remaining capacity, which amounted to 884 kVA, was regarded as the limit for the aggregate EV charging load at the charging site supplied by *civil_engineering_tx1*. In these simulations, a power factor of 1.0 was assumed, simplifying the apparent power limits into active power limits.

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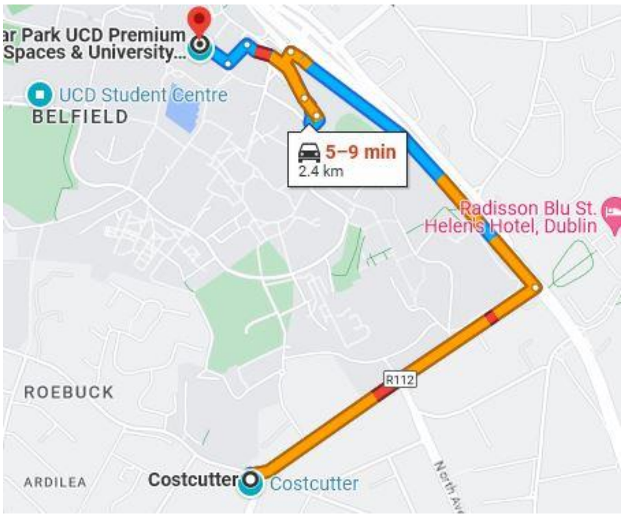

Figure 5. Route from Costcutter to UCD campus parking lot at Veterinary College.

For efficiency and focus, a specific set of representative days were chosen for simulating all scenario variants and operational methods. This involved simulating the first weekday of each month, covering months from January to May and September to December. Additionally, two specific days, one in April and another in October, were selected to represent typical campus conditions during different seasons. This approach provides valuable insights into the implications of the baseline and optimized operation under varied circumstances.

5.3. Simulation Results

This case study utilizes *datafev*, a specialized Python framework designed for testing management algorithms specific to EV charging infrastructure [20]. *datafev* is employed to simulate the controlled operation of charging locations within the UCD campus network. It takes as input: (1) the specifications of the charging sites, including the number and types of chargers at each site in the test ecosystem, (2) the initial estimated departure times and target SOC for the EV fleet using the campus network, (3) power consumption constraints derived from non-EV loads and transformer capacity. Using this information, *datafev* establishes event-driven behavior through object-oriented simulation models. Depending on the defined management approach (i.e., either baseline or optimized in this case study), the objects representing decision-making entities apply the corresponding decision algorithms available in the *datafev* portfolio.

Figure 6 illustrates the power flowing through three MV/LV transformers on two of the simulated days (left for April and right for October). The dashed lines represent the transformers' power ratings, while the green curves depict the aggregate non-EV electrical load measured, as recorded by the respective transformers in the past. During this measurement date, this section of the UCD network did not have any charging infrastructure, so the green curves signify the non-EV load within the simulated scenario. It is evident that the non-EV loads do not impose a significant strain on any of the grid components. However, as the EV penetration rate reaches 50%, the net power flowing through the transformers experiences a notable increase. Transformer *richview_tx1* is particularly impacted in this scenario. Under baseline operation—where drivers select charging sites randomly, and charging profiles are optimally scheduled to prevent transformer overloading—the loading peaks at 116% of the transformer's capacity, with transformer *richview_tx1* operating beyond 100% for nearly six hours.

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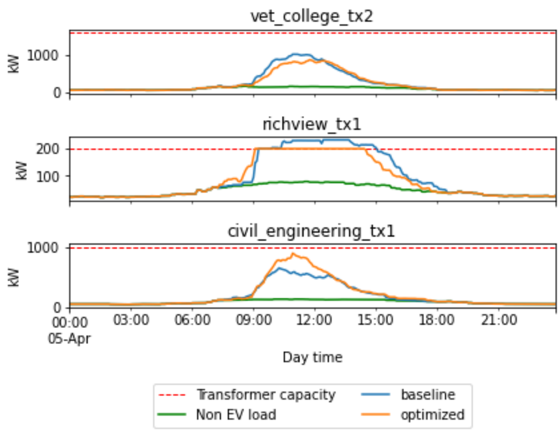
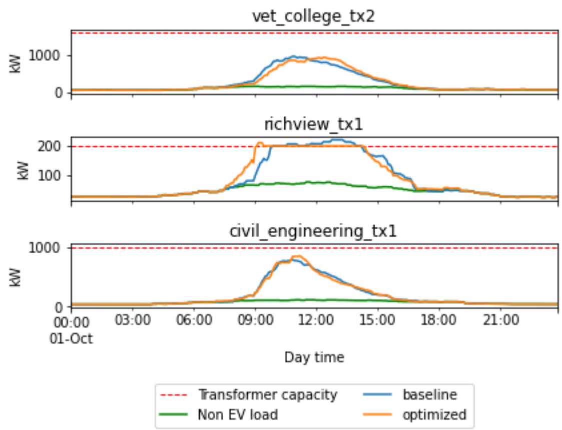
Conversely, the CSS strategy, which redistributes a substantial portion of the load from *richview_tx1* to *civil_engineering_tx1* transformer, stabilizes the peak loading at 100%. A similar situation arises on October 1st, where overloading in *richview_tx1* is slightly less pronounced.



(a) April 5th



(b) October 1st

Figure 6. Load distribution in UCD campus on representative Spring and Fall days.

Figure 7 offers a comparative representation of the MV/LV transformers' loading in Feeder 4, contrasting baseline and optimized operations, on the annual scale. Each column in the figure corresponds to a specific transformer. The histograms present the distribution of transformer load percentages, with the horizontal axis depicting the transformer loading as a percentage and the vertical axis indicating the frequency of these loading levels.

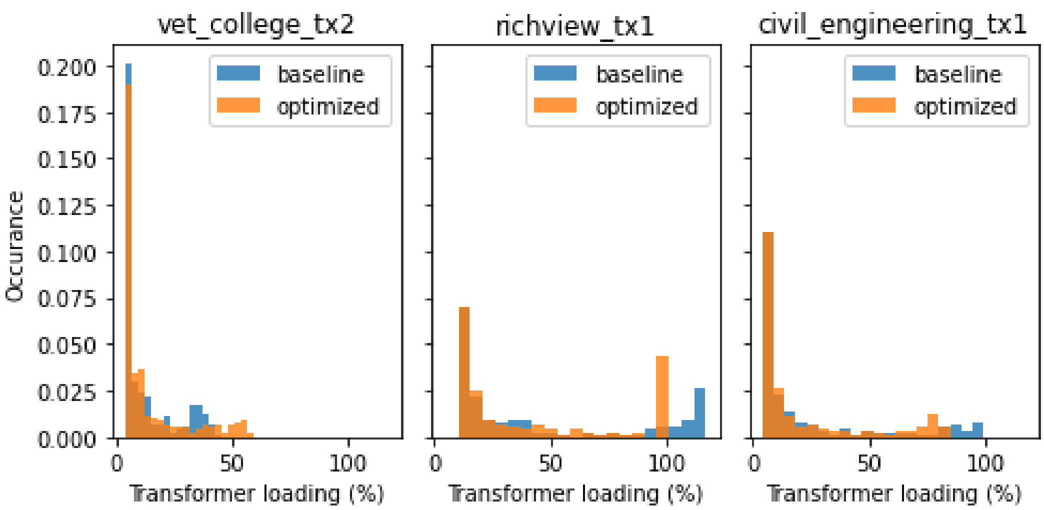


Figure 7.Transformer loading histograms for 50% EV penetration scenario in UCD network.

The optimized operation notably eliminates overloading issues in *richview_tx1*. While the peak observed in this transformer is 116% under baseline operation, the optimized strategy reduces the peak to 100% level. The histograms show that this is achieved by a load redistribution with the peak load of *vet_college_tx2* moving from the 45%-50% range to the 50%-55% range due to the optimized allocation of EVs. However, even with this shift, the peak load remains below the transformer capacity limits. In summary, the histograms of transformer loading illustrate a consistent pattern of load redistribution from overloaded grid sections to those with available capacity.

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While previous research [19] raised concerns about the risk of frequent overloading for transformers *richview_tx1* and *civil_engineering_tx1* in a 50% EV penetration scenario, the conducted simulations demonstrate that the occurrence and severity of transformer overloading can be significantly mitigated simply by optimizing the charging schedules, as observed in baseline operations. The histograms of *richview_tx1* shows that loading exceeding 100% would be observed only for 10 hours on the annual scale. This can be tolerated in many systems. This finding supports the conclusion that the MV/LV transformers linked to Feeder 4 of the UCD network can effectively handle a 50% EV penetration without limiting the grid's G2V supply. However, the study also provides evidence that the optimized allocation strategy leads to a more equitable distribution of the load among the MV/LV transformers connected to Feeder 4. This suggests long-term advantages, such as a reduction in equipment wear and tear. Furthermore, it is reasonable to expect that the balanced load distribution across different grid parts, enabled by the optimized strategy flexibility clustering strategy (i.e., optimized allocation of EVs into different BTM systems) offers further benefits in scenarios where the EV penetration rates reach more pronounced levels. To be specific, when the charging demand leads to often overloading in transformers, active intervention to the charging load may be necessary to keep the system operable. Such interventions, limiting the power supply to EVs in high-loading periods, can result in reduced energy provision.

To quantify such impact, another set of simulation was performed for 75% penetration scenario. In these simulations, the numbers of EVSEs and EVs presented in Table 1 were scaled. At each simulation time step, the aggregate power consumption of EVSEs were constrained in a way to ensure that the transformers are never overloaded. To ensure a comprehensive representation of behaviors throughout the year, we selected 9 distinct weekdays for simulation purposes. These days encompass one day from each month, excluding June, July, and August, for which non-EV load measurements were unavailable. The purpose of simulating these days is to establish a foundation for extrapolating performance metrics at an annual scale. During the extrapolation process, each of the selected days is considered representative of a specific month, and the performance metrics obtained on that day are multiplied by the number of weekdays in that month. For instance, in January 2019, there were 23 weekdays on the calendar. Therefore, the energy supply observed on January 23rd is multiplied by 23 to calculate the monthly metrics. This procedure is repeated for each month in the analysis. It's important to note that the annual-scale metrics do not account for the influence of summer months and weekends. This assumption is based on the understanding that, given the typical campus occupancy patterns and the academic calendar, charging activity during summer months and weekends would likely be minimal.

As expected, the baseline and optimized strategies led to distinct EV distributions to three charging locations. Since the load demand differed, the frequency and extent to which the operation required load curtailment differed in these two cases. The cumulative annual energy supply to EVs under baseline and optimized strategies (in MWh) are reported in Table 2.

Table 2. Net energy supply to EVs at 75% EV penetration scenario.

Location	Baseline operation (MWh)	Optimized operation (MWh)
vet_college	714	757
richview	226	215
civil_engineering	1012	1000
Total	1952	1972

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Significant improvements are evident in the optimized operation, showcasing an annual energy supply increase of 20 MWh. These findings highlight the effectiveness of local cooperation among various BTM units in augmenting the supply capacity of the shared grid infrastructure. By redistributing the load from high-demand areas to those with available capacity, the strategic load reallocation not only ensures a more equitable and efficient utilization of the charging infrastructure but also substantially reduces instances of load curtailment due to grid limitations. The cumulative impact is the enhancement of the UCD network's service potential and an elevated level of user satisfaction. These observations align with the specific objectives sought in the FLOW project.

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6. Conclusion

With the rapid proliferation of EVs, the EV chargers' density has reached high levels in numerous European urban centers. These charging facilities, equipped with V1G/V2G smart chargers, usher in a wealth of opportunities for their operators. From bolstering power supply security by offering backup power and facilitating islanded operations to enhancing energy autonomy and encouraging local generation self-consumption, V2X-capable chargers mark a significant stride towards a more resilient and sustainable energy landscape.

Intriguingly, V2X flexibility can play a significant role in the broader context of flexible asset aggregation. The aggregation environments can include multiple non-flexible generators or consumers as well as flexible DERs ranging from BESs to multi-energy systems such as CHPs and HPs. While these DERs often operate as discrete entities, their operations can be coordinated at both BTM and FTM levels. The comprehensive body of work presented in this document elucidates the functional and non-functional prerequisites for orchestrating flexible asset operation and introduces coordination strategies, capitalizing on V2X-flexibility to alleviate local grid congestion and elevate the EV charging experience.

To orchestrate the operation of flexible assets, Task 4.5 explores two fundamental dimensions of flexibility within V2X-capable clusters: temporal and spatial. Temporal flexibility entails the capacity to reshape power consumption patterns over time, enabled by precise control over grid-to-vehicle (V1G) and V2G energy transfers. Conversely, spatial flexibility empowers the redistribution of power consumption across different segments of shared grid infrastructure.

Besides presenting various flexibility clustering strategies, this document presents a case study that implements one of the strategies (i.e., optimized allocation of EVs to BTM units) on a scenario derived from the UCP campus, which hosts one of the pilots within the FLOW project. This case study explores how spatial dimension of the flexibility empowers a shared grid infrastructure when the flexible assets are aggregated to optimally match the incoming demand with the best location that can accommodate it. The simulations show that optimized allocation of EVs into charging locations effectively redistributes the charging loads across different grid parts, and thus prevents significant overloading in certain MV/LV transformers of the campus network while increasing the utilization factors of underutilized areas. In high penetration scenarios, this impact can translate into significant increase in the energy supply capacity of the shared grid. These findings underscore the importance of the transformative potential of clustering flexibility of EVs at the FTM level in terms of mitigating local congestion and enhancing the overall EV user experience.

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