A novel smart grid architecture that facilitates high RES penetration through innovative markets towards efficient interaction between advanced electricity grid management and intelligent stakeholders

H2020-GA-863876

Architecture of advanced DFA markets and P2P trading

Deliverable D3.1

Document Information

Scheduled delivery	30.09.2020
Actual delivery	29.09.2020
Version	Final
Responsible Partner	UCY

Dissemination Level

PU Public

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Acknowledgements

The research leading to these results has received funding from the EC Framework Programme HORIZON2020/2014-2020 under grant agreement n° 863876.

Glossary of Acronyms

Project management terminology

Acronym	Definition
D	Deliverable
HLUC	High Level Use Case
MS	Milestone
WP	Work Package
UCS	Use Case Scenario

Technical terminology

Acronym	Definition
AFAT	Automated Flexibility Aggregation Toolkit
AI	Artificial Intelligence
API	Application Programming Interface
ARMM	Advanced Retail Market Mechanism
ATP	Automated Trading Platform
B2B/B2C	Business to Business / Business to Consumer
BIC	Bayes-Nash Incentive Compatibility
BRP	Balance Responsible Party
CA	Clinching Auction
DAM	Data Acquisition Module
DER	Distributed Energy Resource
DFA	Distributed Flexibility Asset
DNN	Deep Neural Network
DR	Demand Response
DSIC	Dominant-Strategy-Incentive-Compatibility
DSM	Demand Side Management
DSO/TSO	Distribution/Transmission System Operator
ECC	Energy Consumption Curve
ESP	Energy Service Provider
ESS	Energy Storage System
EV	Electric Vehicle
FSP	Flexibility Service Provider
FST	FlexSupplier's Toolkit
GUI	Graphical User Interface
HVAC	Heating, Ventilation and Air Conditioning
ICT	Information and Communication Technology
KPI	Key Performance Indicator
MCA	Modified Clinching Auction
MDP	Markov Decision Process
ML	Machine Learning
MM	Market Mechanism
RES	Renewable Energy Sources

RF	Random Forest
S/W	Software
SWOT	Strengths Weaknesses Opportunities Threats
TCL	Thermostatically Controlled Loads
TOU	Time of Use
VCG	Vickrey-Clarke-Groves
VPP	Virtual Power Plant
WEMM	Wholesale Electricity Market Module

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Document History

This deliverable elaborates on D2.2 and contains the detailed architecture design of all WP3 subsystems and their interactions as well as the respective technical specifications emphasizing on the detailed description of WP3 research problems.

Table 1: Document History Summary

Revision Date	File version	Summary of Changes
30/06/2020	v0.1	Draft ToC circulated within all consortium partners
03/07/2020	v0.2	All partners commented on the draft ToC structure.
08/07/2020	v0.3	Final ToC version has been agreed and writing task delegations have been provided to UCY and ICCS.
05/08/2020	v0.4	UCY and ICCS contributed their 1st round inputs and first draft version has been reviewed by UNIZG-FER.
15/09/2020	v0.6	UCY and ICCS addressed internal review comments and contributed their 2nd round inputs.
22/09/2020	v0.7	UNIZG-FER reviewed the pre-final version and provided comments for changes/enhancements.
28/09/2020	v0.9	UCY addressed all comments from the internal review process and forwarded the final version to the coordinator
29/09/2020	v1.0	Coordinator (ICCS) made final enhancements/changes and submitted to ECAS portal

Executive Summary

This report is an official deliverable of H2020-GA-863876 FLEXGRID project dealing with the detailed architecture design of all WP3 subsystems and their interactions as well as the respective technical specifications emphasizing on the detailed description of WP3 research problems. The focus of this document is FLEXGRID High Level Use Case #4 (HLUC_04), which deals with the operation of automated flexibility aggregation as a service to independent aggregators. Three Use Case Scenarios (UCSs) are presented for the optimization of the business portfolio of the aggregator, which consists of end energy users/prosumers and their flexibility assets. The respective algorithms will be implemented in a S/W toolkit (AFAT), which will dynamically interact with the core FLEXGRID ATP.

Chapter 1 is an introduction of this report.

Chapter 2 contains a survey on incentives for providing flexibility (i.e. FlexContracts) and on several types of B2C flexibility aggregation architectures that have been proposed in the international literature and real-life business cases. The goal here is to identify all state-of-the-art research that has been recently conducted in the international academic community, while special emphasis is also given to real-life (business) pilots in order to identify the current state-of-the-art in the commercial domain. Based on this survey work findings and the generic description of HLUC_04 (from previous FLEXGRID D2.1 and D2.2), we then focused on the detailed description of three research problems in chapters 3-5.

In Chapter 3, HLUC_04_UCS_01 is presented and the respective research problem is detailed, where the aggregator optimizes the use of its portfolio in a centralized method, in order to build a sustainable business case based on the interactions with the flexibility market (i.e. responds to FlexRequests published by DSO/TSO/BRPs) and end users. In this scenario, all end users state their flexibility preferences and constraints to the aggregator through (the so called) FlexContracts and the aggregator gathers all this information to solve the optimization problem in a centralized manner.

Chapter 4 focuses on HLUC_04_UCS_03 where FlexRequests are not fixed over a time horizon, but the flexibility market in formulated in a bottom-up approach. FlexAssets of end users participate in the flexibility market via an aggregator entity, which is responsible for bidding on behalf of its entire portfolio. Creating price-quantity pairs in order to formulate a FlexOffer is a challenging task for the aggregator, since the costs and constraints of its DERs have inter-temporal couplings. Moreover, the aggregator's bid must be decided in an online fashion, which means that the available time for computations is very limited. The problem is decentralized as the optimal solution is identified through an iteration process.

Chapter 5 elaborates on the previous two B2C flexibility aggregation architectures by introducing advanced pricing models and auction-based mechanisms. The main difference here is the assumption that end users are strategic, and their behavior deteriorates the social welfare of the proposed B2C flexibility market. In this case, a distributed optimization model and privacy-preserving mechanism is implemented, where users are self-organised.

Finally, in Chapter 6, the operation of the proposed Automated Flexibility Aggregation Toolkit (AFAT) and how the algorithms presented in Chapters 3-5 will be integrated in the toolkit are examined. A high-level abstraction of the Graphical User Interface (GUI) of an aggregator user is described, where the main visualizations within the ATP are stated.

Conclusively, in the following months, FLEXGRID consortium will elaborate on the work presented in this deliverable towards the implementation of the methods and algorithms described in the UCSs and the design of the S/W toolkit (AFAT). WP3 work will be synchronized with respective research work in WP4 and WP5 in order to effectively integrate the B2C flexibility market design into the whole FLEXGRID ecosystem.

1 Introduction

1.1 Description of High Level Use Case #4 (HLUC_04)

This High-Level Use Case (HLUC) focuses on the interaction between ESP/flexibility aggregators[1] and end energy prosumers[2]. Flexibility aggregators are considered as actors, which combine flexibility from energy prosumers and/or consumers and participate in markets as flexibility providers. The aggregated flexibility is sold to different stakeholders like DSOs, TSOs and BRPs, which participate in the markets as flexibility buyers.

The purpose of this HLUC is the operation of automated flexibility aggregation for optimal use of resource availability and maximization of profits for all participants in the portfolio (including the aggregator entity itself). FlexContracts are agreed between end users and the ESP/aggregator, where users' preferences and constraints and compensation schemes are stated. Different approaches, leading to different algorithms are used for the optimal use of distributed flexibility assets and are shown by the development of different Use Case Scenarios (UCSs) as documented in previous D2.1 and D2.2 (in Month 4 and 6 respectively).

In this document, the architecture and subsystems of the three Use Case Scenarios (UCSs) under WP3 are described along with the interactions between actors, the technical specifications, the required datasets, the simulation scenarios and the most important KPIs. Centralized and decentralized approaches are examined, with UCS 4.1 taking a central approach, while UCS 4.2 and 4.3 implement distributed and decentralized methods respectively.

The most important algorithms will be integrated in the Automated Flexibility Aggregation Toolkit (AFAT), where several retail flexibility market pricing schemes and flexibility aggregation models will be implemented.

1.2 Research problems and FLEXGRID research innovation

The research problems addressed in the work of the FLEXGRID WP3 project are the development of innovative bidding processes, allocation rules and communication protocols to enable the optimal participation of DERs and end-users in markets. The aim is to alleviate the stress caused to the grid due to high penetration of RES as well as provide an economically sustainable business model for newly emerging actors (i.e. aggregators).

[1] By the term "flexibility aggregator", we mean the market actor who aggregates distributed flexibility from numerous small-scale end energy prosumers. The main difference with the Energy Service Provider (ESP) actor (cf. FLEXGRID D4.1 w.r.t. to WP4 research work) that we use in FLEXGRID is that the ESP is a company that also owns several types of FlexAssets and thus does not only have a portfolio of end energy prosumers like the aggregator.

[2] With the term "end energy prosumer", we mean the end user who participates in a B2C flexibility market as a customer of a flexibility aggregator company.

Specifically, open research challenges of WP3 include the design of advanced machine learning techniques for the modeling of intelligent agents acting on behalf of end users/participants (DFA agents) and the modeling of real-time and long-term interaction of strategic agents within local/retail/B2C flexibility market[3]. Furthermore, WP3 focuses on the development of learning algorithms for each agent's learning and evolvement and with the characterization of solution concepts of repeated interaction. A significant research topic is the design of market mechanisms and architectures that align the objectives of participating actors and lead to a win-win equilibrium for the whole system (cf. mechanism design theory presented in chapter 5). The goal is to achieve social objectives (energy efficiency and cost-effective RES integration), while simultaneously optimizing local objectives (end-user comfort & profit and aggregators' profit). This type of "win-win" business contexts is a major pre-requisite for the success of FLEXGRID concept.

[3] We use this terminology interchangeably throughout the whole document. By the term, "B2C flexibility market", we want to emphasize on the difference with B2B flexibility market operated by the Flexibility Market Operator (FMO). Thus, "B2C" term refers to the interaction between the aggregator and the end users.

2 Survey on B2C automated flexibility aggregation architectures and advanced DFA markets

2.1 Survey on incentives for flexibility

With the gradual liberalization trend of electricity markets starting from the end of the last century and continuing at a fast pace during the recent years, generation, transmission, distribution, and retail activities have been separated and new actors have been introduced in the smart grid and energy market ecosystem.

Traditionally, the development of the electricity markets centered on the role of the supply to meet the demand needs. The rapid development of Distributed Energy Resources (DERs), the electrification of the transportation and heating/cooling sectors and the evolvement of ICT equipment has led to the inclusion of demand side/end users in the planning of a balanced and stable electricity network. Control of DERs can help absorb variability and uncertainty to maintain the constant balance between demand and generation and alleviate congestions/constraints on the transmission and distribution network. Various methods for modifying electricity demand, Energy Demand Management/Demand Side Management, have been examined, proposed, and implemented. In recent years, trading flexibility as a distinct commodity is explored with the suggestion of the operation of local flexibility markets [1] [2].

Flexibility has always been needed and used in power systems. Traditionally, existing market players, mainly producers, provide flexibility to the system and are compensated based on availability (i.e. capacity products) or on dispatch/activation (i.e. energy products) of conventional units through reserve and balancing markets respectively [3]. As wholesale electricity prices from centralized markets are dynamic, market participants can organize their portfolio to exploit the flexibility of their assets. However, one of the main objectives of local flexibility markets is to deal with congestion and voltage control issues in the distribution network. This requires the use of flexible assets, supply and demand, at the distribution network level. These assets usually belong to end users in the residential and industrial sector and their capacity is not sufficient for direct participation in the wholesale market. Nowadays, the wholesale electricity market has dynamic prices, which allows large-scale participants to optimize their portfolio to profit from the dynamic nature of these prices.

During the last years, DERs of end users can be indirectly represented in the market by other market actors through aggregation. Electrical suppliers/providers aggregate end users' consumption, Virtual Power Plants (VPPs) aggregate distributed generation resources and in the market operation proposed by FLEXGRID, flexibility aggregators will aggregate the flexibility from flexible assets, generation, consumption, and storage, and represent them in existing wholesale energy markets as well as emerging flexibility markets proposed by FLEXGRID.

With trading flexibility as a distinct commodity in the wholesale market, flexibility aggregators are expected to profit from optimally orchestrating the management of their portfolio. The profit should sustain both viable business models for the flexibility aggregators and provide incentives for end users, who act as flexibility providers.

In [4], the authors examine the incentives of Demand Response (DR) schemes. The offered motivations for DR are categorized in i) time-based or price-based DR and ii) Incentive-based DR. In the first category, consumers are charged with time-varying prices based on different electricity costs for different periods. In incentive-based DR schemes, reduction of electricity usage is motivated during periods of system stress through fixed or time-varying payments. Constraints and penalties for not participating can occur in specific programs of incentive-based DR.

Incentive-based programs are more suitable for aggregation of flexibility assets and representation in flexibility markets. The authors in [4], further divide incentive-based programs in classical programs and market-based programs. In classical programs, consumers receive participation payments, while in market-based programs participants are rewarded based on their performance, that is the amount of reduced electricity during critical conditions. The categories of incentive-based DR schemes investigated in the paper are Direct Load Control, Interruptible/Curtailable Load, Emergency DR Programs, Capacity Market Program, Demand Bidding and Ancillary Service Market.

The structure and clearing method of Local Flexibility Markets will determine the potential for profits for market participants. In [2], the authors review the concepts, models and clearing methods of Local Flexibility Markets.

Existing electricity wholesale markets have two dominant pricing methods, i.e. uniform price, and pay-as-bid. In [5], proposals of local flexibility markets' design together with respective pilots and business cases are reviewed. A summary of the remuneration, pricing rule and price formation are shown in Table 2.

Table 2: Remuneration, Pricing Rule and Price Formation of flexibility market proposals in the EU area [5]

Proposal	**Remuneration**	**Pricing Rule**	**Price Formation**
Bne Flexmarkt	Dispatch payment	N/a	Regulated
SINTEG C/sells: Altdorfer Flexmarkt	Availability payment	Pay-as-bid	Free with regulated elements
SINTEG C/sells: ReFLEX Dillenburg	Availability payment	Pay-as-bid	Free with regulated elements
SINTEG C/sells: Comax	Dispatch payment	Pay-as-bid	Regulated
SINTEG WindNode: Flexibilitätsplattform	Dispatch payment	Pay-as-bid	Regulated
SNTEG Enera: Flexmarkt	Dispatch payment	Pay-as-bid	Free with regulated elements

SINTEG New 4.0: ENKO	Dispatch payment	Pay-as-bid	Regulated
DA/RE	Dispatch payment	Pay-as-bid	Regulated Free*
Nodes Market	Dispatch payment Availability payment	Pay-as-bid	Free
Grid Integration	Dispatch payment Dispatch and availability payment	Pay-as-bid	Free
GOPACS/ IDCONS	Dispatch payment	Pay-as-bid	Free
Piclo Flexibility Marketplace	Dispatch payment Availability payment Dispatch and availability payment	Pay-as-bid	Free

* *DA/RE* focuses on the coordination of resources that are included in administrative, cost-based congestion management. They are compensated accordingly. Still, *DA/RE* also includes other resources and allows free price formation for them.

The operation of local flexibility markets determines how flexibility aggregators and direct market participants will interact with the market and profit from flexibility trading. The contracts that aggregators have with flexibility providers are, however, not fully discussed.

End users will sign up FlexContracts with flexibility aggregators. A FlexContract will contain end users' preferences and constraints and define the incentives for providing the usage of flexibility assets to the aggregator. The incentives will be a combination of three basic elements, namely: participation, availability, and activation payments. In a non-competitive market, i.e. presence of only one aggregator, pay-as-bid schemes are suitable. However, in a competitive market, further incentives should be provided for end users and thus market competition should be modelled[4].

In the FLEXGRID project, different types of FlexContracts will be examined and evaluated, especially for HLUC_04_UCS_01, where the optimization of the distributed flexibility assets' usage is carried out in a centralized manner.

2.2 Survey on B2C flexibility aggregation architectures

In an electricity market environment with high RES penetration, an important asset is the load flexibility at the demand side. More precisely, Distributed Flexibility Assets (DFAs) are distributed ESS and smart devices that exhibit flexibility in their energy demand (e.g. EVs and HVAC units). DFAs are envisaged to participate in electricity markets through flexibility aggregators[5]. Academic research was quick to design optimization and control methods for

[4] Mathematical models and algorithms for this case are investigated in WP4 (for ESP actor) and are out of WP3 research scope.

[5] By the term "flexibility aggregator", we mean the market actor who aggregates distributed flexibility from numerous small-scale end energy prosumers. The main difference with the Energy Service Provider (ESP) actor (cf. FLEXGRID D4.1 w.r.t. to WP4 research work) that we use in FLEXGRID is that the ESP is a company that also

extracting the value of flexibility from multiple small-scale DFAs. However, actual end user[6] engagement is yet to catch up in the real-life business of flexibility aggregators. During the last decade, a significant barrier has been the lack of intelligent S/W agents that negotiate with aggregators on behalf of the end user and deliver an attractive trade-off between energy consumption/prosumption profile and energy bill reduction. However, advanced modelling tools from Artificial Intelligence (AI) are now able to bridge this asymmetry, while advancements in digital economies are ready to facilitate real time market interaction between intelligent end user agents and intelligent aggregator agents. In this way, aggregators can buy flexibility from DFAs[7] (through a B2C flexibility market proposed by FLEXGRID) in order for the former to be able to enhance their position in B2B markets and increase their profitability, while offering services to the grid. In order to design such B2C flexibility markets, novel Market Mechanisms (MMs) need to be designed. A MM includes the bidding protocols for the market participants and the rules of market operation, namely an allocation rule and a pricing rule. Traditional, static retail pricing schemes are not able to capture the dynamics of the electricity network and thus traditional utilities fail to catch up with the new needs of the energy market. In contrast, dynamic MMs are needed in order to efficiently manage DFAs. A MM can be: i) *Iterative:* Traditional time-of-use (TOU) MMs are open-loop, in the sense that the end user is insulated from the other users' actions (this lack of feedback and coordination between users is a major source of instability) and ii) *Online:* There is inherent uncertainty in the electricity grid, partly because of imperfect forecasts about the inflexible part of user demand and partly because of uncertainty in the supply side. A dynamic MM needs to be able to adjust to online signals in real-time. On the other hand, dynamic/intelligent MMs need a corresponding intelligence on the end user side in order to function properly. For example, an end user that is manually making decisions (cf. manual DR programs) cannot catch up with an iterative online MM. This means that intelligent S/W agents have to be developed on the end user side, to be able to negotiate on behalf of the end users.

2.2.1 Survey on novel market mechanisms for Demand Side Management applications

From a research perspective, Market Mechanisms (MMs) for electricity grids can be generally evaluated through seven basic requirements (or else Key Performance Indicators - KPIs):

1. **Optimality/efficiency**: The difference between the value that all users give to their Energy Consumption Curves (ECCs) (often called utility) and their energy cost (this difference is also noted in the literature as Social Welfare).
2. **Incentive Guarantees/Strategy proof**: The resilience of the system to users who benefit from declaring false preferences. In other words, a MM should ensure that end users benefit from declaring their truthful preferences.
3. **Privacy protecting**: The quantity of information that is required from the end user in order for the MM to operate properly. A novel MM should ensure that the end user's

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owns several types of FlexAssets and thus does not only have a portfolio of end energy prosumers like the aggregator.

[6] With the term "end user", we mean the end energy prosumer who participates in a B2C flexibility market as a customer of a flexibility aggregator company.

[7] An end user/energy prosumer may own several DFAs. In FLEXGRID research, we either assume a FlexOffer per DFA or an aggregated one per end energy prosumer according to the research problem that we investigate.

preferences are not disclosed to the aggregator or else that the aggregator cannot infer the end user's preferences in the whole process of the proposed B2C flexibility market.

4. **Convergence/scalability**: The speed of convergence of a MM and its scalability with respect to the number of end users. This KPI is especially important for aggregator's participation in near-real-time electricity markets (e.g. balancing), because the proposed MM should be able to run quickly and provide valid results.
5. **Fairness**: The policy for distributing the energy costs and awards to end energy prosumers should be fair so that it is also able to trigger behavioural changes (e.g. in distribution level flexibility markets proposed by FLEXGRID). For example, end users would be unwilling to participate in Demand Response events if not-participating or cheating users benefit from them. Moreover, with the term "fairness", we mean that each end user should be compensated according to the (exact) amount of flexibility that s/he offered to the aggregator.
6. **Competitiveness/economic sustainability/practicality**: The MM should offer to the end users (prosumers) attractive charges with respect to their ECC, while being practically implementable/realizable in real-life conditions. In other words, it is very important that a novel MM does not require advanced (and thus) expensive ICT equipment, so that many end users can easily buy the required equipment and participate in the proposed B2C flexibility market.
7. **Externalities**: Other positive/negative outcomes of the MM (e.g., controllability in order to satisfy system-wide constraints, simplicity for users to understand the mechanism, how the MM decisions affect the local distribution network operation in terms of possible local congestion and voltage control issues, etc.).

Optimality/efficiency is of great importance, especially for policy makers and market operators. It refers to eliminating market inefficiencies. When there are parties on both sides of the market that would agree to trade at a given price, but the trade does not happen for some reason, we say that this market is inefficient. Flat retail prices, as well as static Time of Use (TOU) prices, create market inefficiencies since the real-time prices of the market are essentially invisible to the demand side. Thus, real-time pricing was the first to be considered in the academic literature for advanced and automated DSM schemes. In particular, [1] proposed a MM and the Lagrange multipliers for the dual problem were interpreted as the retail market prices. Then, an iterative algorithm is proposed that converges to the prices that maximize social welfare without considering any other KPI.

Incentive Guarantees/Strategy proof refers to the issue of taking advantage of the market mechanism by a strategic end user in order to maximize his/her profits. More specifically, the studies in [5], [7], [8] assume that end users are price-takers (i.e. an individual user's load is very small compared to the entire aggregator's portfolio and thus his/her behaviour does not affect the prices). Nevertheless, there are several use cases in which the price-taking behaviour assumption is not valid like for example regarding: i) large industrial consumers, ii) users that participate in DSM in a particular geographic location where network congestion problems occur, iii) islanded RES micro grids formed at neighbourhood level, etc. In these cases, the users are expected to behave strategically and strategic behavior may compromise the market mechanism's efficiency. In [9], the issue of strategic behavior was tackled by proposing a Vickrey-Clarke-Groves (VCG) approach for retail electricity trading. The VCG mechanism is widely considered as the cornerstone of mechanism design as it is provably the unique mechanism that achieves the optimal social welfare (cf. 1st KPI mentioned above), while also providing the strongest incentive guarantee (2nd KPI), which is Dominant-Strategy-Incentive-Compatibility (DSIC) as extensively explained in [10]. However, the VCG mechanism comes with serious disadvantages in almost all the other KPIs (e.g. privacy, competitiveness, etc.). A case against the VCG mechanism is also made in [11]. In this study, a simpler, clock-proxy auction was proposed that tackles the issue of strategic users who might apply a bid-parking strategy. In addition, the budget balanced nature (i.e. competitive MMs) of this work and of more recent works such as [12] and [13] offer much more competitive MMs.

Regarding **user's privacy protection**, a distributed mechanism is proposed in our work [14], which is presented in chapter 5 below, where an optimal market mechanism was designed based on Ausubel's clinching auction [15]. The proposed mechanism guarantees the DSIC property and does so in a distributed fashion. Integrated with a privacy-preserving communication protocol (an example based on [16] is also described in [14]), the mechanism can bypass the privacy issue of the direct VCG mechanism, while preserving its desired properties.

Other challenges are **the fairness and the scalability of MMs**. A mathematical approach towards a solution for the scalability of MMs is proposed in [17], where smoothing techniques are applied to the objective function of the optimization problem in order to facilitate fast convergence. A different approach is taken in [18], where groups of users with similar characteristics are considered as an aggregated participation. While this approach might create minor inefficiencies, it drastically reduces the MM's convergence time. A different objective is considered in [19], where the social welfare efficiency is partially relaxed for the sake of fairness and competitiveness. In particular, the study demonstrates that there is a trade-off between these two KPIs. The Shapley value concept extensively described in [20] from cooperative game theory is used to define a fairness index and the mechanism is accordingly designed to maximize fairness. A privacy-preserving implementation is also proposed, which comes with a compromise on the fairness objective.

Other special properties required in each use case are categorized under the "umbrella" term of mechanism **externalities** (cf. 7th KPI). For the sake of being more specific, we present the two following examples. The first example is when system-wide constraints on users' consumptions might need to be satisfied. In [21], the coordination among users is taken into consideration and an architecture is proposed that satisfies what is formally called coupled constraints. Another example of special requirement relates to the market mechanism simplicity (easy user adoption). The studies presented above provide some strong theoretical guarantees under certain assumptions. A central assumption is the rationality of the end-user behaviour. However, in practice and especially when it comes to residential user participation, we cannot expect the users to always behave rationally when facing complicated mechanisms that they do not fully understand. Thus, a relevant requirement relates to the mechanism's plain simplicity. For example, in [8], MM is optional towards simplicity and in [22], selection process facilitates user interaction.

Based on all the above-mentioned international literature, we observe that very elegant models have been proposed towards the integration of MMs in the retail electricity market and in DSM applications. However, there are two major research directions that still remain relatively unexplored and it is FLEXGRID's aim to investigate. The first refers to the design of market mechanisms that jointly consider the KPIs presented above and achieve an attractive trade-off among many or all of them. The second refers to designing market mechanisms that are able to tune these trade-offs on demand according to the aggregator's policy. Finally, within the FLEXGRID architecture and business ecosystem, the proposed B2C flexibility market will be able to interact with all the other B2B markets, meaning the aggregator's participation in existing transmission-level markets as well the proposed FLEXGRID distribution-level flexibility markets.

2.2.2 Survey on intelligent S/W agent solutions for end energy prosumers

The section refers to a literature review on the level of intelligence at the end-user's side (i.e. Distributed Flexibility Asset /DFA agents). Only a few of the studies mentioned above (e.g., [11] and [21]) provide an online implementation of the MM they propose, while all the others propose offline implementations. In addition, the algorithms governing user decisions are *myopic*, i.e. they best-respond at each market instance without considering uncertainties about future interactions. However, advances in Artificial Intelligence (AI) can already offer the required intelligence for the DFA agents to capture the stochastic nature of the market. In [23], it is shown that end users' S/W agents that consider the stochastic nature of the environment yield better quality schedules than those obtained from a deterministic model. In particular, Markov Decision Processes (MDPs) [24] are the prevailing modelling tool to describe the decision making of a foresighted agent in a dynamic environment. Especially in multi-agent environments, such as a local flexibility market, the settings can be modelled as Stochastic Games, Bayesian Games or Evolutionary Games depending on the setting's properties, e.g., the local information available to the end-user agent, the level of communication available, etc [10]. The relevant literature exhibiting applications of such techniques in the DR domain is quite recent and not particularly rich. The authors in [25] designed an algorithm for making decisions about whether to store energy from surplus local RES generation, or consume it using controllable loads. The underlying optimisation problem is a sequential decision making process under uncertainty. The authors proceeded to designing a technique that handles the intractability of the MDP and present an approximate dynamic-programming method to achieve a fast response. Similarly, the authors in [26] approximated an intractable MDP via a method based on Bellman-error estimation. Moreover, they considered fully foresighted users that can learn to better schedule their loads in a partially observable stochastic game. In contrast to the equilibrium solution concept of [26], the authors in [27] considered a centralized heuristic method for end user decisions.

In general, the vast majority of studies in AI-assisted DSM (for example see [[29] [30] [31] [32] [33]) consider static environments (e.g. with simple time-of-use prices) where the agent's decisions do not have an effect on the MM's price. This is not accidental, since studying a holistic multi-agent game is remarkably challenging as the theoretical tools available for studying such a setting are still in their infancy. More specifically, from a technical perspective, there are well-developed tools for:

- Studying the strategic interaction of a set of cooperating or competing players (cf. game theory)

- Designing systems for incentivizing coordination in such settings (cf. auction theory and mechanism design)
- Optimizing the evolvement of strategic decisions of an agent in an unknown, stochastic environment (cf. Reinforcement Learning techniques such as Q-learning)

But when it comes to a setting involving strategic intelligent agents (i.e. agents with the ability to learn) that interact in a stochastic environment, serious complications arise for the above methodologies. For example, when the rewards of one agent are coupled with the actions of another, the environment becomes non-stationary, i.e. the knowledge learnt by the agents may become inaccurate over time (because of the evolving behaviour of other agents), and they need to acquire new knowledge to adapt to these changing conditions. A comprehensive review of recent literature in this field [34] underlines the lack of holistic, non-stationary, multi-agent frameworks for intelligent DSM, and most importantly the need for pilots that integrate learning algorithms with actual real-user feedback.

Regarding FLEXGRID research, the challenge here is to model the objectives of both intelligent, foresighted end users and the aggregator in the wholesale market. In other words, it remains an open challenge to integrate intelligent algorithms for DFAs' decisions with dynamic MMs designed to serve the aggregators and ultimately the underlying physical electric grid.

2.2.3 Summary of FLEXGRID R&I novelties/contributions

Open research challenges that will be addressed within FLEXGRID WP3 work include: i) design of advanced AI techniques to model intelligent agents that act on behalf of each end user/ participant (DFA agents), ii) modelling the real-time and long-term interaction of these strategic agents in the context of a local/retail or else B2C flexibility market, iii) development of learning algorithms for each agent's learning and evolvement, iv) characterization of the solution concepts (equilibria) of the repeated interaction, v) design of mechanisms and architectures that align objectives and lead the whole system to a win-win equilibrium in which social objectives (energy efficiency & cost-effective RES integration) are achieved while local objectives (end-user comfort and ESP's profitability) are optimized. According to these, the following figure depicts high-level interactions between the DFAs, end energy prosumers, aggregator and the various markets in which the aggregator may participate within FLEXGRID context.

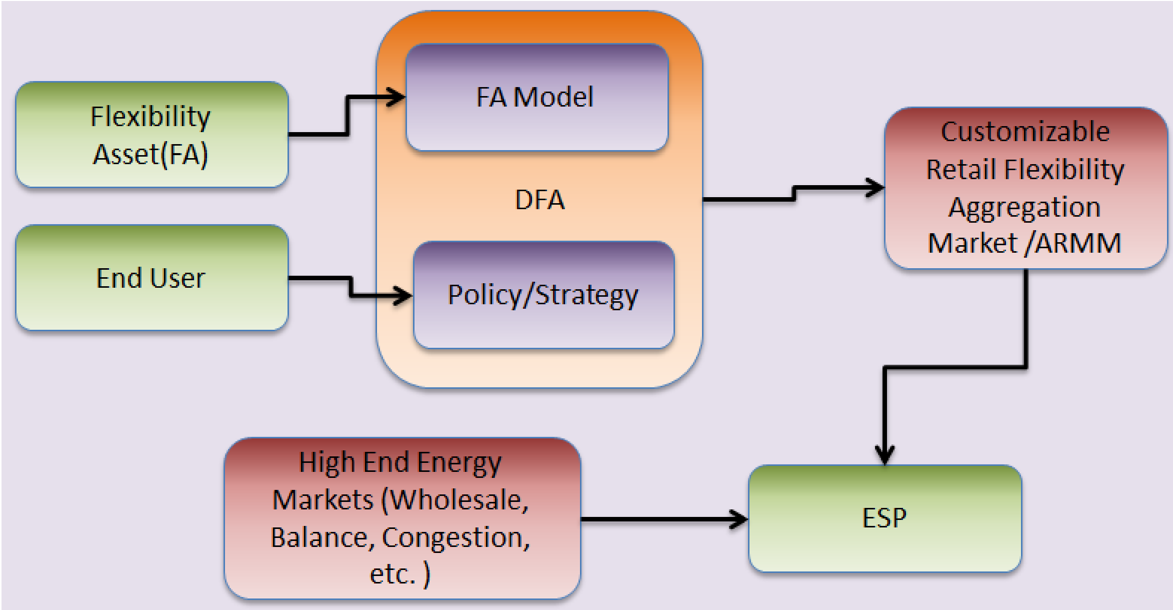

Figure 1: Automated B2C flexibility aggregation architecture proposed within FLEXGRID

In order to tackle the above-mentioned challenges already stated in the most recent international literature, FLEXGRID will draw on concepts from the areas of Game Theory, Auction Theory, Mechanism Design, Artificial Intelligence and Multi-Agent Systems. In particular:

- FLEXGRID will develop a meta-service able to automatically transform utility functions of FlexAssets (e.g., ESS, EVs, DSM assets) to FlexOffers through the design of advanced DFA models by: i) translating the capabilities of the existing FlexAssets to the needs of the markets in order to allow stakeholders such as aggregators and ESPs to participate in them without having deep technological background, and ii) composing FlexAssets (e.g., combination of curtailments from DSM with shifts through the use of ESS, etc) in order to meet the requirements of FlexOffers. In this way, DFA owners (or else end energy prosumers) not only can participate easily and without technical background in the future electricity markets (both existing at the transmission network level but also new emerging ones at the distribution network level), but also to maximize their revenues in those markets (cf. optimal FlexAsset exploitation).

- FLEXGRID envisages the composition and the proposition of Advanced Retail Market Mechanisms (ARMMs) for the aggregator's/ESP's B2C flexibility market, to buy flexibility from the DFAs. This tool will receive the aggregator's/ESP's position in the wholesale market (e.g. deviation from day-ahead dispatch & real-time pricing signal) as input and tune the parameters of the proposed B2C flexibility market mechanism accordingly. In other words, the proposed ARMMs will offer to aggregators/ESPs the ability to achieve an attractive trade-off between the aforementioned requirements (KPIs) and prioritize the KPIs that are more important to them by sacrificing the less important ones. This strategy is derived from the expertise of the FLEXGRID consortium that testifies to the contradictive nature of these KPIs (e.g. auction algorithms that ensure incentive guarantees are not competitive/budget balanced). A primary objective of FLEXGRID's ARMMs is to achieve the development of retail policies able to dynamically reflect the wholesale and real time market prices (for balance and congestion) to the end users' payments. In a nutshell, FLEXGRID will develop: i) bidding processes, ii) allocation rules, iii) communication protocols and iv) peripheral components towards the next generation retail pricing schemes through the use of recent advances in algorithmic game theory and auction theory.

- On the DFAs' side, FLEXGRID will design algorithms for optimizing the long-term DFA's strategy in this dynamic and stochastic market environment. That is, the DFA agent will keep track of its own bids in the proposed B2C flexibility market and associate them with the consequent outcome of that day. Thus, in a period of several days, the DFA agent will learn to optimize its bidding strategy, to make sure that it achieves profitability without sacrificing user comfort. Towards the end, the learning algorithms will be able to incorporate actual user feedback to be able to be tested in a real-life environment after the end of project's lifetime. Thus, FLEXGRID will be able to contribute towards bridging the gap between academia and industry and paving the way for new and more economically sustainable investments in distributed FlexAssets.

3 An Aggregator efficiently responds to FlexRequests made by TSO/DSO/BRPs by optimally orchestrating its aggregated flexibility portfolio of end energy prosumers

The focus of HLUC_04_UCS01 presented in this Chapter is the central optimization of the utilization of DERs/FlexAssets in flexibility markets by a flexibility aggregator. In centralized optimization schemes, all decisions of distributed assets are made centrally, by the aggregator, in contrast with distributed and decentralized approaches (cf. models in chapters 4 and 5 below).

3.1 Research motivation and novel FLEXGRID contributions

The specific nature of the electricity market necessitates a constant balance between supply and demand. The stability and reliability of the electrical grid depend on the maintenance of this balance. Uncertainty in the electricity sector is increasing both on the supply and on the demand side with penetration of intermittent renewable sources and introduction of new types of demand [34].

System operators are responsible for the balance of the system which is traditionally achieved by contracting centralized large-scale generators. Electrification of the transportation, heating, and cooling sectors in combination with the digitalization of the energy sector enables balancing actions and create new opportunities on the demand side as well. This new type of potential balancing units is typically distributed and cannot individually participate in the electricity market but can be represented through aggregation.

Uncertainty in the electricity market can be absorbed by flexibility markets where supply/demand flexibility is traded as a commodity and services are offered to deal with congestions and network planning. The main motivation for the development of flexibility markets is achieving system balance without requiring high investments in grid infrastructure. However, the operation of this new type of market in a liberalized environment creates opportunities for other actors beside system operators. Flexibility can satisfy, as mentioned, technical needs concerning system operation (TSO/DSO), provide better balancing opportunities for trading (BRP) and provide the requirements for non-dispatchable generation (RES) to participate in energy markets.

Flexibility markets will work in parallel with existing energy markets and will allow the participation of new types of assets in the wholesale market. A flexibility aggregator is a new type of actor and is considered as an independent actor with no other role in the energy market. The independent aggregator is responsible only for the aggregation of flexibility assets and their representation and utilization/operation in flexibility markets. This necessitates a co-operation with other actors (Suppliers, BRPs) which represent the same assets in different types of markets. Sustainable business models need to be identified for trading in the flexibility market.

A **novel B2C flexibility market** is proposed within FLEXGRID project, which can operate in unison with existing electricity markets. The used approach aims to maximize the aggregator's profit by optimally scheduling the operation of the flexibility assets within its portfolio and transforms citizens to active consumers, through aggregation, in accordance to the European directive [35].

3.2 Survey on related works in the international literature

The work presented here focuses on centralized optimization of aggregated distributed flexibility assets, both supply and demand, in flexibility markets. Related work can be found in studies on aggregation methods, demand side management and demand response, distributed level management, and flexibility and flexibility markets.

One distinct method of aggregating distributed resources is via a Virtual Power Plant (VPP). As presented in [36], the basic concept in VPPs is to aggregate distributed energy resources, with focus on distributed generation and participate on their behalf in wholesale electricity markets. In [37], the authors focus on a VPP, which consists of prosumers and the goal is to coordinate for better results in demand response requests. This approach takes advantage of economy of scale; however, flexibility is not traded as a commodity.

In [38], the authors classify distribution-level energy management approaches into four general classes: top-down switching, price reaction, centralized optimization and transactive control and coordination. They consider that transactive control and coordination offers the best advantages for integration of flexible devices. In their approach however, distributed resources are not aggregated for reserve purposes.

In [39], an optimal bidding strategy for day-ahead markets is presented which considers demand flexibility. This method requires a dual role for the aggregator whose portfolio should fulfil the requirements for participation in wholesale markets.

The authors of [40] compare economic and environmental drivers for demand-side aggregation and include carbon emission trading as another potential for income for changes of the consumption pattern.

The authors of [41] study the operation of local flexibility markets to address DSO needs in order to avoid additional investments and thus the focus is on potential types of flexibility requests according to the grids needs.

In [42], the coordinated participation (optimal bidding) of aggregators in wholesale energy markets and local flexibility market is presented. Once again, this approach requires the aggregator to be eligible for participation in energy markets and requires a dual role. In the method presented here, it is assumed that different prices in day-ahead markets can be obtained through day-ahead flexibility requests.

3.3 System model and problem statement

In case of a flexibility need, there can be an adjustment on the supply and/or on the demand side. For an upward flexibility request, the supply needs to be increased. This means that the generation activated to respond to the flexibility request should not have been included/sold in any previous energy markets. On the other hand, demand needs to decrease in the case of an upward flexibility request. Contrary to supply, the consumption of any load, which will be adjusted to serve the upward flexibility request should have been included in the forecasted demand (energy exchanges). In a similar manner, in the case of a downward flexibility request, supply needs to decrease, and demand needs to increase. The decrease of supply can only be performed by generation units which were scheduled to generate, while increase of demand can be achieved by loads, which were not scheduled to consume. This is especially important when the flexibility assets are not represented by the same actors in the energy market. This stands for both energy and capacity of the flexibility assets.

The baseline is defined as the originally scheduled production/consumption pattern of an asset. The aggregated baseline is the aggregated curve from all flexibility assets in the portfolio of the aggregator. This aggregated baseline curve is represented by the appropriate actors in wholesale energy markets. The cost of the aggregated baseline at time t is the electricity price at time t times the scheduled consumption at time t. The total cost of the aggregated baseline is the summation of these products. Scheduled supply from generation and discharging storage units are included in the cost function and are expressed with negative values, as negative demand. Due to the aggregator's representation of end-users, the assumption is that demand flexibility assets will exceed supply flexibility assets. However, focus from demand to supply can be changed, according to the composition of the portfolio of the aggregator.

A flexibility request can either be a request for activation of energy (upward or downward) for a timeslot/s or a request for available capacity for a timeslot/s with a potential activation request if required. In the first case, the compensation will be based on the activated energy (dispatch payment). In the second case the availability of the capacity will be compensated and potentially the activated energy as well (availability payment/dispatch and availability payment).

An upward flexibility request with compensation for energy activation at time t, which can be matched with a flexibility offer in the portfolio of the aggregator will bring in revenue the flexibility request price times the upward activated electricity volume. The profit of the response to the flexibility request is:

$$P_d = D_f * \lambda_f - d_f * \lambda_g$$

It should be noted here, that D_f is positive and it is the total decrease of aggregated demand, d_f is the decrease of consumption of flexibility assets, while λ_f and λ_g are the energy prices in the flexibility market and the wholesale energy market respectively. Increased supply is not included in the aggregated baseline, thus in the cost. However, there is a potential cost introduced by increasing supply, which should be considered and depends on the activation/adjustment and operational costs of supply units.

The response to a respective downward flexibility request is more complex. The compensation of the energy activation with a positive downward flexibility price, translates to payment of increasing consumption and decreasing production. Negative prices in the market can occur [43] and should be accounted for but should not be considered the norm. The profit from a response to the flexibility request is:

$$P_u = U_f * \lambda_f - u_f * \lambda_g$$

Here, U_f is the total increase of aggregated demand and u_f is the "increase" of production from flexible supply assets, while λ_f and λ_g are the energy prices in the flexibility market and the wholesale energy market respectively. As supply units in reality reduce their supply, the "increase" of production has a negative value. Increased demand from flexibility assets, which participate in the offer have not been included in the aggregated baseline. Reduced operational costs from the adjustment of supply units can be considered as an extra revenue.

The aggregator, depending on its portfolio, can respond to flexibility requests for capacity availability. As stated above, such a request will involve availability payment and potentially dispatch payment in case of activation of the flexibility. To accept this type of requests, apart from dispatch payments which were considered in flexibility requests concerning energy activation, availability payments should be included in the cost function as well. If the aggregator responds to/accepts such a request, the requested capacity needs to be available at all periods defined by the contract, regardless of activation. A flexibility aggregator can ensure that the aforementioned capacity is available by appropriately managing its portfolio.

In order to successfully respond to a flexibility request or a request for energy activation of available capacity, an appropriate mix of flexibility assets needs to be selected and matched to the requirements of the flexibility request. The direction, the flexibility price, and the requested capacity/energy as information contained in the flexibility request have already been briefly addressed. Other fields are also required to select suitable flexibility assets. The basic information contained in a flexibility request is depicted in Figure 2, while in [44], one may find the exact data model used by NODES market today.

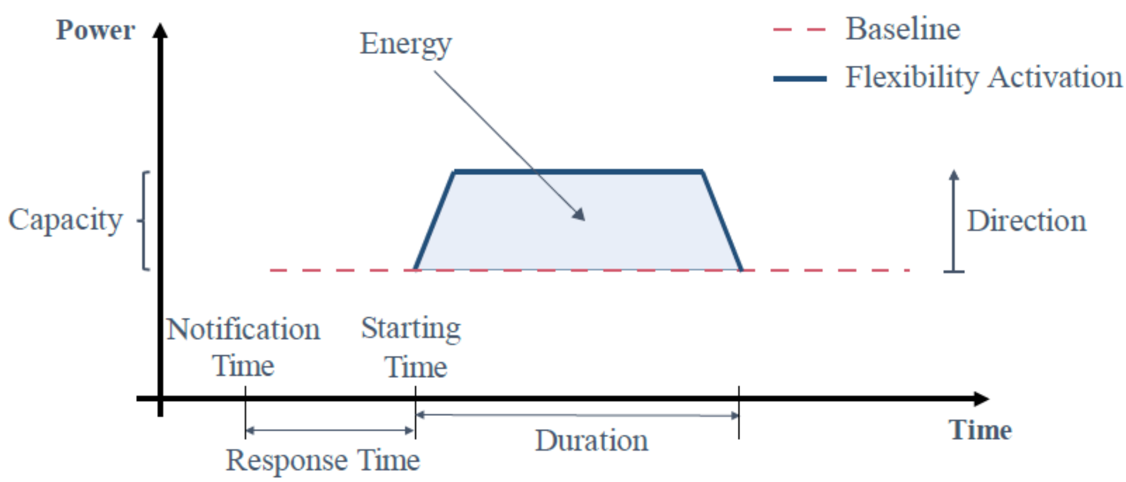

Figure 2: Attributes of a FlexRequest (indicative example) [45]

The identification of suitable flexibility offers within the portfolio of the aggregator to match the flexibility request requires the ability to extract the same attributes contained within a flexibility request from the available information of the flexibility assets.

The aggregator's portfolio consists of several types of flexibility assets. A first classification is made based on the type of asset: generation, storage, and load. Generation units can be distinguished to dispatchable and non-dispatchable. Curtailment of intermittent renewable energy, as stated earlier, is a solution that should not be prioritized, thus only dispatchable generation units can be realistically considered as flexibility assets. Intermittent generation sources can contract flexibility, according to expected forecasting error, to reduce expenses in balancing markets or to be rendered dispatchable and enabled to participate in energy markets. It is possible for intermittent generation sources to be part of the aggregator's portfolio, and their flexibility needs can be met within the same portfolio. Without loss of generality however, it will be considered that intermittent renewable sources do not belong to the portfolio of the aggregator, but function as external flexibility buyers.

Loads can be divided into three categories: adjustable, shiftable and non-adjustable. As stated by the name, the consumption pattern of non-adjustable loads is not subject to change. Non-adjustable loads, by definition, are not included in the portfolio of the flexibility aggregator. Both adjustable and shiftable loads are considered demand flexibility assets, however they have different flexibility behaviors. It is assumed that alteration of the consumption pattern of adjustable loads for a certain time window is not propagated; potential rebound effects are not taken into consideration at this stage. This means that before and after flexibility activation, the consumption of the adjustable load will coincide with the baseline. Adjustable loads can be activated either for upward or downward regulation.

On the other hand, the total energy consumption of shiftable loads is simply shifted in time, thus the consumption of a shiftable load can be advanced or postponed in respect to its scheduled operation in the baseline. Activation of a shiftable load outside the scheduled operation time can contribute to downward regulation while the consequential deactivation of the load at the scheduled operation time provides upward regulation. Any rescheduling of shiftable loads in response to flexibility requests should ensure positive profit from both downward and the corresponding positive regulation. Two categories of shiftable loads are considered: continuous and interruptible.

Storage units are ideal flexibility resources. The bidirectionality of storage units renders them capable for both upward and downward regulation. In both cases their consumption/production pattern is not included in the baseline, thus they do not incur cost in energy markets to offer flexibility in either direction.

A basic assumption is that all flexibility resources are equipped with the appropriate ICT infrastructure which allows them to be controlled remotely.

3.4 Problem formulation and algorithmic solution

The information contained within a flexibility request and the types of flexibility assets were described in the system model. As stated in the previous section, the aggregator should adequately extract the same type of information from flexibility assets to respond with appropriate flexibility offers. This determines the necessary fields requested from flexibility providers concerning their flexibility assets.

The parameters of flexibility assets can be distinguished in two classes: technical parameters and user preferences parameters. Technical parameters include among others, response time, amount of power/energy, duration capability, controllability, current state/status, and location. These parameters are needed to check the technical aspects of matching a flexibility request. User parameters are required to customize the objective function of end-users and to build different types of user profiles. User parameters include baseline consumption and cost, retail pricing scheme, acceptable deviations from baseline consumption, constraints, and comfort level.

Parameters can be given for single or combination/aggregation of flexibility assets depending on the level of controllability.

The objective function of the aggregator is to maximize the profit from participation in the flexibility market. Revenues of the flexibility aggregator are dispatch and activation payments, while the expenses are the costs of acquiring and activating flexibility from end-users. The cost of flexibility acquisition and activation involves both “actual” costs, i.e. market and retail price, and costs determined by users’ preferences. The total monetary cost of a flexibility asset is defined by FlexContracts with end users and is known a priori.

A FlexContract, as stated in Section 2.1, will be potentially composed by a mix of: participation payment, availability payments and dispatch payments. The FlexContract ensures that each user is compensated minimally the amount covering his cost and discomfort, thus minimum pay-as-bid. Within the FlexContract, constraints of the user’s assets are specified as well, such as number of activations within a time frame and deadlines for shiftable loads.

In this manner, three different optimization problems can be considered. The first involves the optimal selection of a subset of flexibility assets for activation, with given flexibility activation requests and FlexContracts. The second concerns the selection of which Flexibility Requests to respond to, in the case where not all Flexibility Requests can be satisfied simultaneously. Finally, the third case is the customization of FlexContracts/expansion of portfolio.

The simulation horizon for delivery is a 24-hour day divided in hour, 30-minute or 15-minute timeslots as in existing markets. Flexibility requests can be long-term, medium-term and short term. Requests will take place both in previous day of delivery (day-ahead requests) and on the day of delivery (intraday, near-real-time). Day-ahead requests will contain needs for flexibility adjustments for the entire delivery day, while flexibility requests on the day of delivery will refer to a specific timeslot. A flexibility request can either contain a request for potential activation (capacity) or certain activation (energy).

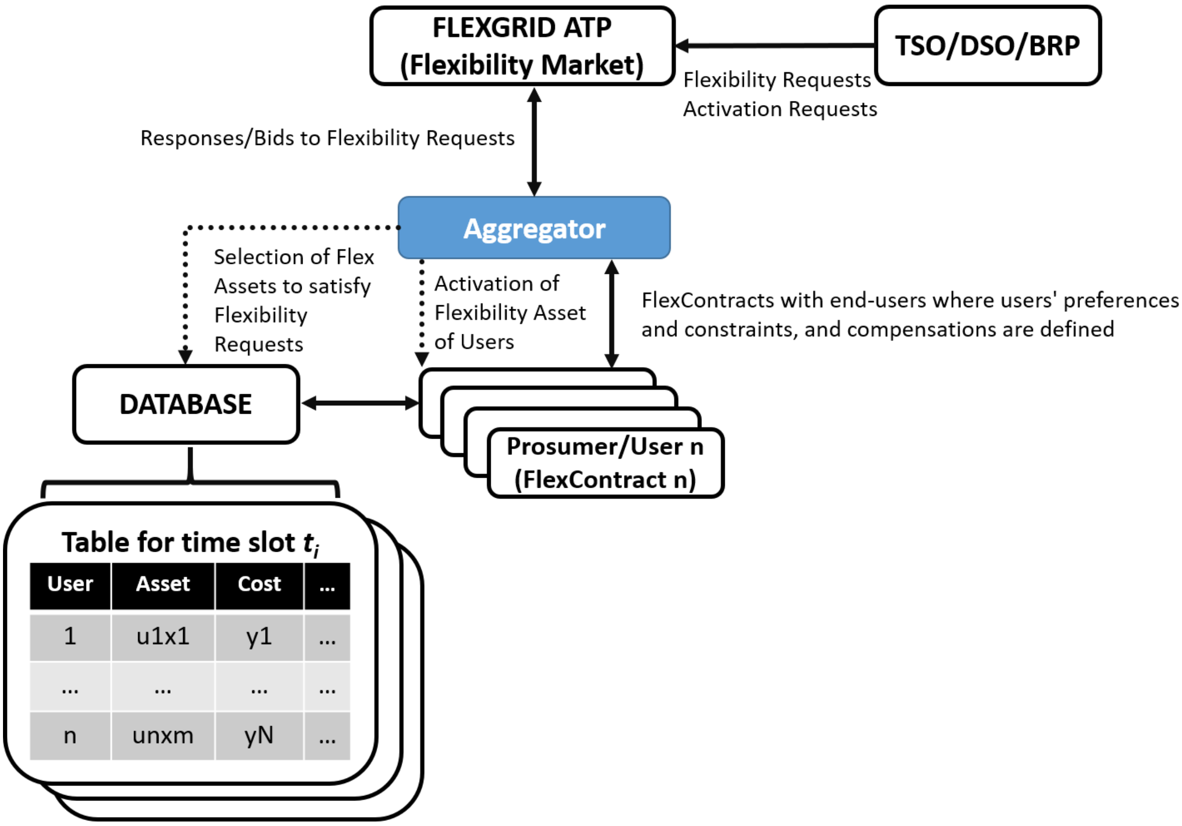

Figure 3: Proposed system model for aggregator's participation in the flexibility market

3.4.1 Optimal selection of flexibility assets for activation

Based on the FlexContracts of the users, the cost of each flexibility asset can be determined for each time slot and its effect in future time slots. Given a sequence of requests for activation of flexibility and flexibility obligations of the aggregator (available capacity), the aggregator needs to optimally select the appropriate subset of flexibility assets in order to minimize the cost.

Exhaustive search will be used to determine the optimal solution, which will be used as a reference point. However, it is expected that exhaustive search algorithms will be time demanding and will lack in scalability. The efficiency of greedy scheduling techniques and dynamic programming will be tested in performance and scalability.

The output of this evaluation scenario is the optimal subset of activated flexibility assets for each time slot.

3.4.2 Selection of Aggregators Responses to Flexibility Requests

Given a sequence of flexibility requests where the aggregator cannot respond to all the requests due to lack of resources, the aggregator needs to select the optimal subset of requests to respond to. For the acceptance of flexibility requests for available capacity, the aggregator should be able to activate the required capacity for the worst-case scenario. The objective function is to maximize the profit, thus, to increase the revenues from responding to flexibility/activation requests considering the cost and constraints of each flexibility asset.

The output in this case is the set of Flexibility Requests which maximizes the profits of the aggregator.

3.4.3 Customization of FlexContracts/Expansion of portfolio

Based on the outputs of the two previous optimization problems, the aggregator can customize FlexContracts to increase the flexibility of certain users to either minimize the cost of activating flexibility assets or to expand its portfolio to be able to respond to more flexibility requests.

3.5 Datasets and most important KPIs

Datasets that are required as inputs in the simulation setup are:

- The consumption baseline of flexibility assets for the simulation horizon
- Parameters of flexibility assets (technical and user preferences)
- Market prices for the consumption baseline of flexibility assets
- Realistic scenarios of flexibility requests (capacity needs, activation needs and flexibility prices)

The consumption baseline can be derived with a combination of past demand data and types of assets in the portfolio of the aggregator while realistic values will be taken (from literature) for the technical and user preference parameters of flexibility requests. Data required to include flexibility requests in the simulation environment will be extracted with assumptions from existing energy and capacity market prices (mainly day-ahead, reserve and balancing markets).

From the aggregator’s perspective, the most important KPIs are the maximization of profit, the reliability/reduced risk of representing distributed flexibility assets, scalability and customer engagement. End-user’s most important KPIs are privacy, profit, and comfort level.

4 Aggregator maximizes its profits by dynamically orchestrating distributed FlexAssets from its end users to optimally participate in several energy markets

4.1 Research motivation and novel FLEXGRID contributions

The increasing penetration of Renewable Energy Sources (RES) in modern power systems necessitates the need of flexible energy resources that can provide services towards continuously balancing supply and demand. To this end, the flexibility capability of small, distributed energy resources (DERs) is considered an important asset that needs to be utilized effectively.

Integrating DERs into the wholesale electricity markets has been a much-discussed topic in the power systems community [46]. There is a general consensus that participation of DERs should be realized via aggregators, i.e., entities that participate in electricity markets and undertake balance responsibility on behalf of a portfolio of multiple DERs [8] [47]. The portfolio of an Aggregator may consist of small generation facilities (predominantly RES), distributed storage, and controllable electricity consuming assets such as Electric Vehicles (EVs) and Heating, Ventilation, and Air-Conditioning (HVAC) units.

A DER is assumed to be registered with an aggregator, where the latter installs the necessary communication infrastructure that allows it to monitor, forecast and control the electricity profile of the DER. Each DER has a certain set of preferences towards its electricity profile, as well as a cost function that maps a DER's electricity profile to a monetary cost. For example, an EV has an arrival time and a certain energy that it needs to receive (charge) before its departure. If the aggregator requests the EV to receive less energy than required, then the EV agent requests a compensation for this flexibility service.

Market participants (buyers and sellers) can trade energy in the day-ahead and/or intra-day markets. This free trade, stops at a certain time before real time (delivery time) in order for the system operator to make sure that the system will be balanced in real time operation. The time in which the trading stops is called gate closure time. After gate closure, each participant has a certain energy profile (energy bought/sold), which needs to be reported to the system operator. This profile is referred as the participant's “market program”.

In real-time operation, the operator of the electricity system (i.e. TSO) is responsible for maintaining the balance between supply and demand. Given a market program for each market participant, the TSO receives the players' offers for providing or requesting balancing energy. An optimization problem is run at the TSO side, through which the balancing energy dispatch of each player is determined in the most cost-effective manner.

In order for the TSO to be able to solve this optimization problem in a fast and scalable way, the balancing energy offers made by the participants need to be provided in a certain bidding format, which makes sure that the optimization problem is tractable. For example, a participant is typically required to make an offer for upward balancing energy and downward balancing energy for the timeslot ahead. An offer is a mapping that relates a level of balancing energy provision to a certain monetary cost. These offers are typically required to be in a step-wise form, i.e., pairs of price-quantity.

Aggregating the DERs' preferences and capturing the aggregated flexibility costs is a difficult task. The difficulty mainly lies in expressing the flexibility costs and local constraints of multiple DERs into an **informative but concise** offer/bid that the TSO will be able to incorporate in its dispatch problem. Moreover, the dynamic nature of DERs requires that all necessary computations must run in **real-time** in order for the aggregator to dynamically adjust its bids in the balancing market. Finally, it is desirable that the aggregation method is **general** enough (i.e., not tailored to a specific DER model), so that different types of DERs can register and participate. These four requirements for the aggregator's bid **(i.e. concise, informative, real-time, general)** and their importance are described in detail in [48].

4.2 Survey on related works in the international literature

Different aggregation methods have been proposed in various studies. In [49], the energy requirements of a set of EVs is communicated to the electricity market by constructing a set of upper and lower bounds for the aggregated demand across time. Once the aggregator receives a (aggregated) power dispatch, the power is allocated to the EVs via an auction procedure. In [50], an aggregator is providing reserves on behalf of a DER portfolio. An inner-box method is used to aggregate DER constraints. The method takes the DER constraints as input and outputs the upper and lower bounds on aggregated net load (considering also time-coupling constraints).

Another family of studies considers the case where an aggregator acts as a Virtual Power Plant by representing a set of DERs in the market. In electricity markets, where a certain participant holds considerable market power, bi-level optimization approaches have shown that the participant's profit can be optimized. In [51], bi-level programming is used to derive the optimal offering strategy of a DER Aggregator in a day-ahead electricity market. However, the cost of flexibility for the demand-response assets is neglected in the model. In [52], a bi-level program is again used to maximize the aggregator's profits in the day-ahead market, while also considering the cost of demand response.

On the other hand, in electricity markets with high levels of competition, it is to the best interest of each participant to bid according to its marginal cost [53]. In such settings, many studies consider the aggregator as a "price-taker", that has a certain forecast of the electricity price and only bids an energy quantity. In [54], a stochastic mixed-integer linear program is solved in order to calculate the optimal bid of a DER portfolio in the day-ahead market, assuming a price forecast. In [55], an EV aggregator defines its optimal bidding curve, again assuming certain knowledge about electricity market prices. A similar approach is taken in [56], where the aggregator stochastically optimizes its quantity-only bids in the DA market and real-time market.

However, a quantity-only bid communicates that the player is willing to buy/sell this quantity at any price, which is a case that is more relevant to suppliers / load serving entities / retailers. In contrast, since the real-time balancing market prices can be volatile, flexibility aggregators could benefit from bidding price-quantity pairs.

Fewer studies have considered an Aggregator that bids in the real-time balancing market. In [57], an EV aggregator is in charge of participating in the day-ahead and real-time (balancing) market on behalf of an EV fleet. However, the aggregator only bids the desired energy quantity and not a price-quantity function. In [58], a stochastic bi-level mathematical program is used for optimizing the strategy of a price-taking DR aggregator in a real-time market. In [59], an EV-fleet Aggregator bids in the day-ahead and real-time market on behalf of the EVs. An optimization problem is solved based on the probability distribution of real-time electricity prices, which is assumed known. In [60], a microgrid aggregator bids an energy quantity in the real-time balancing market and an event-driven mechanism is applied to the DERs in order to incentivize them to comply with the cleared aggregated quantity.

Summarizing the literature review, studies typically assume some type of electricity price forecast, and a price-taking aggregator that only bids an energy quantity (much like a supplier) instead of price-quantity pairs. **Creating price-quantity pairs, is a challenging task for the aggregator, since the costs and constraints of its DERs have inter-temporal couplings**, i.e., the flexibility cost of a DER in the current timeslot is dependent on how the DER flexibility will be controlled in future timeslots. Moreover, the Aggregator's bid must be decided in an online fashion, which means that the available time for computations is very limited.

To this end, learning methods have been studied as a way to facilitate fast decision making in online operation, after having been trained offline. In [61], a deep reinforcement learning method is proposed, through which a price-making aggregator decides for its energy bids in a day-ahead electricity market. In [62], a neural network is trained to learn how the aggregated consumption of DERs changes with a set of retail prices imposed by the aggregator to the DERs. A similar model is used in [63], where the authors also used particle swarm optimization to determine the aggregator's optimal retail price vector that maximizes its profit. However, these studies, again, have not provided a method for the aggregator to capture its flexibility costs in price-quantity pairs.

4.3 System model and problem statement

In FLEXGRID, we take into consideration the above-mentioned four requirements towards designing an aggregator’s FlexOffer as follows (cf. also [48]):

- **Req #1: The aggregator’s FlexOffer should be concise.** Given the scale of aggregators and the complexity of the constraints of FlexAssets, it is impossible to communicate precise information about every FlexAsset. Instead, aggregate flexibility feedback must be a concise summary of a system’s constraints. Even if it was possible, providing exact information about the constraints of each FlexAsset governed by the aggregator would not be desirable because the FlexAsset constraints are typically private.

Information conveyed to the system operator must limit the leakage about specific FlexAsset constraints[8].

- **Req #2: The aggregator's FlexOffer should be informative.** The feedback sent by an aggregator needs to be informative enough that it allows the system operator to achieve operational objectives, e.g., minimize cost, and, most importantly, guarantee the feasibility of the whole system with respect to the private FlexAsset constraints.
- **Req#3: The aggregator's FlexOffer should be general enough.** Any design for an aggregator's FlexOffer must be general enough to be applicable for a wide variety of controllable loads, e.g., electric vehicles (EVs), heating, ventilation, and air conditioning (HVAC) systems, energy storage units, thermostatically controlled loads, residential loads, and pool pumps. It is impractical to imagine a different FlexOffer for each FlexAsset, so the same design must work for all distributed FlexAssets.
- **Req #4: The aggregator's FlexOffer should be real-time.** The system is time-varying and non-stationary and so it is crucial that (nearly) real-time feedback can be defined and approximated if it is to be used in online FlexOffers made by the aggregator.

In FLEXGRID, we propose a generic method for capturing the aggregator's upward and downward flexibility cost for a set of DERs that have non-convex models and inter-temporal couplings. The method is model-free in the sense that it is not tailored to any specific DER model. Rather, it can be applied to any use case of DERs, regardless of the DER models. We use a fitting function for this purpose. In order to address the uncertainties of the DERs' parameters, we perform offline scenario-based simulations, and use these simulations to train a machine-learning (ML) algorithm. Different ML methods are tested and compared. In online operation, the trained ML can be provided with the current state of the DERs, and predict the optimal aggregator's FlexOffer (prices for given levels of balancing energy) for the next timeslot ahead very quickly and, as our simulation results indicate, with very good accuracy.

We consider a DER aggregator, which is responsible for submitting offers for energy flexibility on behalf of its portfolio. A set of FlexAsset owners/end energy prosumers (via respective S/W agents) is registered with the aggregator for a particular time horizon. The portfolio has a particular market program (i.e., the energy bought in the day-ahead market) for each timeslot of the horizon.

Some agents can offer certain flexibility with respect to their electricity demand. In particular, the electricity consumption of a flexible agent can be controlled. A consumption profile that is different than the agent's uninterrupted consumption, comes with a cost for the agent. Moreover, each agent bears a set of constraints regarding its profile.

The aggregator has to provide a bid/offer regarding its flexibility in the next timeslot (i.e. a cost for energy injection and an offer for energy absorption). The bidding format is subject to the rules of the market operator. Typically, it has to be in a form of a step-wise function that defines pairs of balancing energy and price, in order to make the economic dispatch problem solvable by integer programming methods.

[8] A similar approach may be followed for an aggregator's FlexOffer in the novel distribution-level flexibility markets (DLFMs) proposed by FLEXGRID.

Subsequently, the TSO gathers all the offers for balancing energy and clears the balancing market close to real-time, i.e., decides the balancing energy dispatch of each participant and the balancing energy price. Upon receiving the dispatch order, the aggregator calculates the power of each DER to minimize the cost of flexibility procurement. The procedure is visualized in the following figure[9].

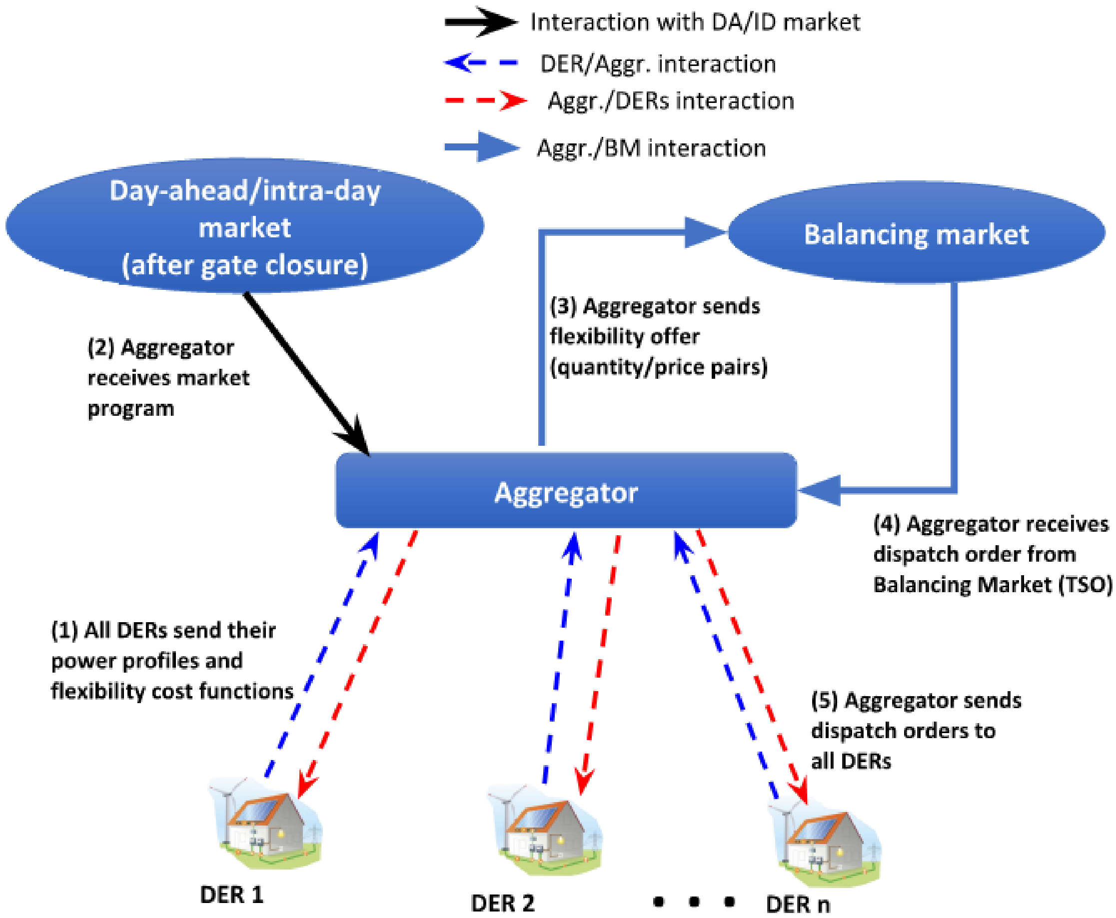

Figure 4: Proposed system model and steps for aggregator's participation in energy markets

This bidding format, although conducive for the TSO, is quite restrictive for the aggregator, since it cannot fully capture the aggregator's actual model, which is comprised by the cost functions and constraints of all agents in the aggregator's portfolio. Note also, that the agents' cost functions may exhibit inter-temporal dependencies. Thus, the problem of the aggregator is to find the suitable bidding co-efficients for the next timeslot ahead, that best express its actual flexibility costs.

4.4 Problem formulation and algorithmic solution

In FLEXGRID, we opt for designing a method that is model-free in the sense that it can be applied, regardless of the specific form of the agents' flexibility cost functions. Moreover, by

[9] It should be noted that by the term "balancing market" shown in figure 4, we refer to any near-real-time FlexRequest submitted in FLEXGRID ATP by a given BRP and/or TSO.

auctioning the profile to its DERs through a B2C flexibility market (cf. chapter 5 below), the aggregator can acquire the provisioned flexibility without knowing the DER models. However, extensive simulations may be required before a good approximation is achieved, which can be impractical for real-time operation, since the method becomes computationally expensive.

Therefore, we propose the use of Machine Learning (ML) techniques to train, offline, a decision-making system using various scenarios for the agents' flexibility cost functions as well as their constraints. Once trained, the ML algorithm will be able to provide a fast decision on the FlexOffers for the next timeslot ahead, upon receiving information in online operation.

The task at hand is a regression problem. That is, given a specific input, a set of numerical values are predicted. Various ML algorithms will be tested for this problem such as Deep Neural Networks (DNNs) and Random Forests (RF).

Deep Neural Networks consist of one input layer through which the features are fed into the network. A number of hidden layers follows, each one comprised of several neurons. The large number of layers in DNNs allows the network to learn complex representations. The challenge is to define the number of hidden layers and neurons in order to balance the accuracy and the computational complexity of the model. There is no standard formula to do this, and a "trial and error" approach is usually required. Another typical problem is over-fitting. There are several solutions such as weight decay or dropout.

Random Forests is an ensemble learning method. Ensemble methods use many learning algorithms combined. They obtain better predictive performance when compared to any of the learning algorithms alone. One ensemble method is bagging of classification or regression trees. In this method, successive trees are independently constructed using a bootstrap sample of the data set. A majority vote is taken for the final prediction. Bagging improves the accuracy and also reduces variance and over-fitting. In Random Forests, the best split of a given node is decided using a predictor chosen randomly from the set of predictors of that node. Depending on the specific scenario, they can outperform other regression or classification techniques based on support vector machines or neural networks. More details about the design, development and operation of the above-mentioned algorithmic solutions and respective mathematical models will be extensively described in subsequent WP4 deliverables (i.e. D4.1 and D4.2).

4.5 Simulation setup and performance evaluation scenarios

For the purpose of evaluating the proposed method, we consider a setting, where the aggregator represents a portfolio of flexible loads and a RES generation facility. The aggregator may look several (e.g. five) timeslots ahead. We assume that the aggregator has to submit a FlexOffer for the next timeslot ahead. A flexible load (DER) features an arrival time and a departure time and has a feasible interval for energy allocation.

The portfolio may consist of a few classes of loads, e.g. Thermostatically Controlled Loads (TCLs), including Air-Conditioners, Water Heaters etc., Electric Vehicles (EVs), battery storage units, etc. An EV is constrained by an upper and lower power consumption level and it cannot be charged before arrival or after departure. Moreover, the EV has a certain energy requirement to be fulfilled. When the total charged energy upon departure is less than the requirement, the agent bears a cost.

For TCLs, the transition function of the temperature is defined based on first order dynamics, considering temperature decay (e.g. insulation) and energy conversion efficiency (from electrical power to thermal energy). The TCL has a setpoint which represents the agent's target temperature. The TCL agent’s flexibility cost function is defined on the basis of its deviation from the setpoint temperature.

The aggregator also features local RES generation facilities. We assume probability distributions for these parameters and sample from the joint distribution. For each sample, we run a number of experiments, where in each experiment we use a different aggregated profile and obtain the flexibility cost. Similar constraints are also applicable for the battery storage units. For example, among others, each battery cannot be charged above/below a certain level (i.e. capacity), the charging/discharging rate is specific, and the degradation factor is given by the manufacturer.

In order to evaluate the proposed method, we will use a model through which the wholesale electricity market receives the offer of the aggregator and decides whether it is going to request balancing energy (up or down) from the aggregator. In reality, this decision is made by running an economic dispatch problem in which the offers from all market participants are taken into account. We abstract away the complete market model and construct a Wholesale Electricity Market Module (WEMM) that provides decisions only on the aggregator's dispatch and the balancing energy price for the current timeslot.

First, the WEMM receives the aggregator's offers for the timeslot ahead. The module randomly decides if it is going to need upward or downward balancing energy, with equal probability unless stated otherwise. The aggregator is called to offer balancing energy with some probability. In case the aggregator is not able to follow the dispatch order, it suffers an imbalance price. Thus, once the Aggregator receives the dispatch order from the WEMM in current timeslot, it calculates its decisions by solving a profit maximization problem.

4.6 Summary of Key Performance Indicators (KPIs) to be measured

In the above-described simulation setup, we will test the mean and the standard deviation of the score (defined as the Mean Absolute Error) of the ML algorithms for a large number of scenarios. Moreover, we will evaluate the training time of each ML algorithm, as well as its response time in a real-time operation. In particular, the ML algorithm needs to provide a FlexOffer estimate in a dynamic real-time balancing market, which means that it should be able to respond rapidly.

Another KPI is the aggregator’s profits achieved in the simulation setting. The algorithms run for a number of different cases for the imbalance price. For each value of the imbalance price, a number of setting instances are simulated and the results on the aggregator's profits are averaged out over all instances.

We also want to test the success of the ML algorithms towards providing a good estimate of the aggregator’s flexibility costs. Our metric for this, is the number of imbalances that occur after the aggregator is requested to realize its dispatch order (i.e., provide the foreseen balancing energy). If the Aggregator succeeds in minimizing imbalances, this would verify that the proposed ML method achieves a very good capturing of the aggregator's flexibility cost, i.e., the FlexOffers made by the ML method do not result in dispatch decisions that the aggregator cannot follow.

5 An aggregator operates an ad-hoc B2C flexibility market with its end energy prosumers by employing advanced pricing models and auction-based mechanisms

5.1 Research motivation and novel FLEXGRID contributions

Serving the energy demand in peak demand times might be quite expensive for the grid operator because of the need to constantly maintain costly energy reserves. Also, in regions with high penetration of Renewable Energy Sources (RES), adjusting the demand to meet the intermittent generation can enhance the efficiency and economic viability of the system. As a result, the idea of offering monetary incentives (rewards) to consumers in order to decrease their consumption at peak demand times (or else increase their consumption at low demand times) is getting a great deal of attention both from the research community and the industry. Such techniques are generally referred to as Demand Response (DR).

The high penetration of RES in modern smart grids necessitated the development of DR mechanisms as well as corresponding innovative services for the emerging flexibility markets. The dynamic nature of RES generation makes it necessary to design mechanisms that can balance supply and demand in an ad-hoc, real-time framework. More specifically, when there is a need for reducing energy consumption in real-time, an ad-hoc market is created where the operator offers to buy consumption reduction from the users (cf. FlexRequest concept of FLEXGRID). This real-time flexibility market is called a “DR-event”. Thus, the users participate in such a DR event by offering their consumption flexibility in exchange for monetary compensation.

In the near-future smart electricity grid, each user (consumer) is expected to0 have a smart meter that measures his/her consumption at all times. The grid operator can assess the aggregated consumption of users at a particular part of the grid in real-time. Users are interested in their own payoff, which results from the reward they receive and the discomfort they experience from reducing their energy consumption. On the other hand, the operator is interested in the reduction of the aggregated consumption at peak times (or else the increase of the aggregated consumption at off-peak times).

At the same time, developments in computer science, and particularly in Artificial Intelligence (AI), offer the necessary tools for designing intelligent agents that can make fast, adaptive and optimal decisions on behalf of the end user, (for example for controlling the consumption of a HVAC unit or the charging of an Electric Vehicle). Such intelligent agents have already been proposed in the smart grid literature, for home energy management systems [64], and for controlling the behaviour of smart residential appliances [31].

An intelligent agent is characterized by its utility function (or payoff). This function is modeled by the system designer and the agent is programmed to optimize it. The way the designer models the agent's utility function is very important for the success of the designer's goal. In

AI programs, the agent discovers methods to optimize the utility function that is given to it, by learning from data (e.g. machine learning) or by experimenting (reinforcement learning) in the real or in a simulated environment (cf. chapter 4 above). A recurring phenomenon in state-of-the-art AI programs is that the agent discovers unexpected ways to optimize the given utility, which the human designers did not foresee. An example of this phenomenon is the infamous bot in [65], that was told to minimize the contact time between its feet and the ground. The goal was to make the bot walk faster, but it ended up learning to walk on its elbows. Another recent example refers to the creative ways discovered by the bots of OpenAI, to leverage the model's "physics" and optimize their play in a hide-and-seek game [66].

Because of these phenomena, it is important to be very careful in the design of an energy management system with distributed decision-making by intelligent agents. In particular, the utility function that is programmed in the agent, the information exchange, and the multi-agent interaction have to be carefully designed so that the system behaves as intended. *Mechanism design* is a field of game theory, where interaction schemes are studied and evaluated in terms of how well they perform with regards to the designer's objective as well as how the agents' reward structures can be formulated in order to align their incentives with the designer's goal. The latter property is formally called *"incentive compatibility"*.

Assuming strategic user behaviour, the real-time B2C flexibility market setting turns into a game, since each user's payoff is dependent also on the actions of other users. Since the actions of the other users depend on their experienced discomfort, which concerns private information, the DR event is a game of incomplete information. In more detail, discomfort could be modeled through a local function, so that it is expressed in monetary terms.

An intermediate entity is assumed to resolve the formulated game and clear the ad-hoc flexibility market described above. We refer to this entity as the "aggregator". The aggregator is assumed to be an independent entity with the objective of coordinating the flexibility trading in the most efficient way. Formally, in economics, the "most efficient way" is characterized by the concept of maximizing the social welfare, defined as the aggregated payoff of all market participants. Nevertheless, the users' local functions (related to their flexibility/comfort levels and consumption habits) are private to each user. This makes the task of the aggregator quite challenging, especially when considering users, who act strategically and might misrepresent their local function if that makes them better-off.

In FLEXGRID, we propose a B2C flexibility market architecture through which an aggregator will be able to optimally resolve the aforementioned game. In particular, we draw on concepts of mechanism design theory in order to define an iterative, auction-based mechanism, consisting of an allocation rule and a payment rule. The allocation rule refers to the way that the aggregator decides upon how much consumption reduction/increase will be allocated to each user according to the feedback obtained through the auction process. The payment rule refers to the way the aggregator decides upon the reward of each user for his/her allocation, provided that the user makes the corresponding contribution. Through the auction procedure, the aggregator exchanges messages with the users in the form of queries. A query in our case is a price signal communicated from the aggregator to the user, to which the user responds with his/her preferred action (i.e. consumption reduction) according to this signal. Note that a user may respond untruthfully if he/she finds that to be in his/her interest.

5.2 Survey on related works in the international literature

In the DR literature, the end user is typically modeled as a selfish player who participates in the mechanism with the purpose of maximizing his/her own payoff. The user's preferences are widely modeled as a convex function (e.g. [1], [7], [8]). In [67], the electricity bill is minimized while the user's satisfaction is maintained above a defined threshold. In [68], a similar framework was built for deciding the charging times of EVs under forecasted prices. In [47], a spread is applied to the real-time prices in order to penalize deviations from a predefined schedule. In these studies, the bill of a user depends only on his/her own actions and it is disengaged from the actions of others. Thus, the users' DR actions might not be well coordinated.

In [69], the authors assume that consumers voluntarily provide their consumption preferences to a central entity, which optimizes the social welfare. Similarly, in [70], users estimate their energy needs and report them to an aggregator. In [71], a set of users enter into a direct-load-control contract with a load serving entity, responsible to satisfy a DR event. However, in all the above-mentioned works, end users were assumed to honestly reveal their consumption preferences.

In contrast to the studies presented so far, [1] and [7] considered users that do not reveal their local preferences, and the flexibility service prover/aggregator controls their consumption indirectly by iteratively updating prices and observing the aggregated consumption. The authors use a dual decomposition method to discover the optimal prices. A scalable approach is proposed in [72], where smoothing techniques facilitate fast convergence. In [73], the aggregator is modeled as a profit-maximizing entity and a simulated annealing algorithm was adopted for the price optimization problem. The authors in [74] configure the pricing scheme with a forecast component. In [75], the authors consider two simple billing rules and prove that best-response dynamics converges to Nash Equilibrium. In [12] and [13], pricing schemes are deployed with the objective of maximizing the fairness of the consumption allocation. In [76], the effect of the FSP's profit policy on the DR outcome was examined. However, in all the studies of this paragraph, end users are assumed to truthfully best-respond to each price query, and thus they don't compromise the algorithm's properties.

In mechanism design terms, the above mechanisms are not incentive compatible, because a strategic user can benefit by manipulating his/her responses. Note that the optimality guarantees of the above studies, would no longer hold in the case of strategic end users. When considering strategic users, the mechanism designer is confronted with a trade-off: the Vickrey-Clarke-Groves (VCG) mechanism is the unique welfare maximizing mechanism implemented in dominant (and not best-response) strategies [77], meaning that either a VCG approach is taken (like in [9], [78]) or welfare maximization is compromised (like in [79], [80] [81] [82].

The main problem with the direct-revelation VCG approaches (such as [9], [78]) is that they require end users to reveal their whole set of preferences to the FSP/aggregator, while the latter makes all the calculations and decides the allocation and the rewards. This is clearly impractical, since real end users cannot compactly express their preferences in closed-form mathematical functions and even when they can, they are not happy to compromise their privacy. These issues were also reported in [22] and [83], where the authors proposed that the available actions for each end user were restricted to a predefined set in order to simplify the message space. However, the authors in [83] do not model the effect of the user's actions on the price (similarly to [67] [68] [47], and the authors in [22] consider EV-charging users who are only interested in the overall energy consumption over the horizon (which is not suitable for other loads and neither for en-route charging EVs). Naturally, these kinds of approximations result in loss of efficiency.

A distinct family of studies has elaborated on how the consumption measurements of an individual user can be masked in order to protect the user's privacy (e.g. [84]). In [85], a distributed authentication method is proposed, while [86] exploits hash functions in order to serve secure data transmission. Furthermore, [87] evolves load hiding techniques and [88] proposes obfuscation technologies towards data privacy. In [89] and [90] , the authors propose privacy-preserving data aggregation methods with minimum overhead, while [91] also accounts for the case of a malicious FSP. Finally, [92] exploits adaptive key evolution, while [93] and [94] focus on the consensus problem towards reliable communication in fully distributed systems. However, the studies of this family do not contribute to the design of the pricing scheme per se and assume that prices only depend on the aggregated consumption. This class of pricing rules can result in an optimal allocation under assumptions but it is not incentive compatible.

Within FLEXGRID context, we propose a **novel B2C flexibility market architecture**, which:

- is suitable for a distributed implementation (unlike [9] and [78],
- achieves the VCG outcome and does not sacrifice efficiency (unlike [79] and [82], and
- is incentive compatible (unlike [1] [7] [67] [76] [85] [94].

5.3 System model and problem statement

In this research problem, we consider a B2C flexibility market architecture comprised of an aggregator and a set of self-interested consumers (i.e. end users or else end energy prosumers). Each user possesses a number of controllable appliances, with each appliance bearing an energy demand. Since demands of different appliances are assumed independent and are not coupled, we can consider one appliance per user for ease of presentation and without loss of generality. Thus, we will use the terms "user" and "appliance" interchangeably throughout the whole residual chapter.

An appliance requires an amount of energy for operation. For example, if an appliance's operating power is 1Watt, and s=1 hour, then the energy that the appliance consumes in one timeslot of operation is 1Wh. This energy consumption is measurable in real-time and can be shed if the user wishes. In particular, we consider controllable loads, meaning that the user can modify consumption upon request, in exchange for monetary compensation. Such a request for consumption modification is called FlexRequest[10] (or more generally a DR event). Upon a FlexRequest asking for reduction of the real-time consumption, the user can respond by reducing his/her consumption by a certain quantity.

The user (or the user's agent) experiences a certain discomfort due to consumption curtailment. The discomfort function is private to each user and expresses the minimum compensation in monetary units (e.g. euros) that a user requires, in order to reduce his/her consumption by the corresponding amount. The discomfort function can take various forms, depending on the appliance. In order to incentivize users to reduce their consumption, the aggregator offers a monetary reward. A user's utility is defined as the difference between his/her discomfort for the consumption reduction realized and the reward he/she received for this reduction.

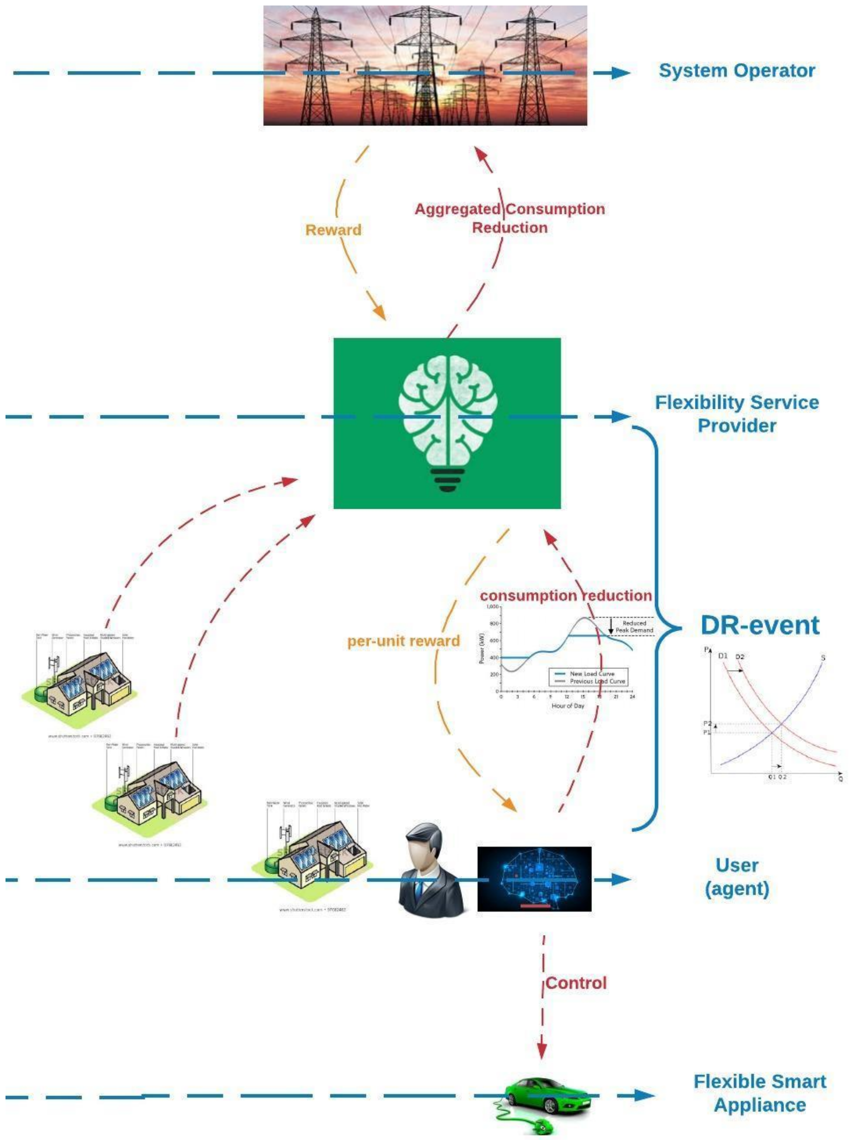

Figure 5: System model for the realization of the proposed B2C flexibility market architecture

[10] Within the FLEXGRID project's context, a FlexRequest may be generated by a DSO, TSO or BRP.

Upon a FlexRequest, the operator (e.g. the DSO that operates the distribution grid) asks for a reduction of the users' aggregated consumption during a certain time interval and offers monetary incentives to the aggregator towards its realization. The incentive (reward) is implemented as a per-unit compensation for the electricity units of reduced consumption. Thus, we assume that upon a FlexRequest, the operator offers a marginal per-unit reward for various levels of consumption reduction.

The aggregator is responsible for aggregating the users' participation in the FlexRequest, coordinating their actions, and allocating the compensation profits (rewards) among the users. We assume a communication network, built on top of the electricity grid, through which the aggregator can monitor each user's consumption and exchange messages with the users. The system model is depicted in the following figure.

With respect to the mechanism that the aggregator uses to clear this real-time B2C flexibility market, we opt for a VCG-like approach to achieve social welfare maximization, but we omit the direct-revelation approach of the typical VCG mechanism. Instead, we design an iterative auction mechanism based on Ausubel's clinching auction, in which users are only required to make decisions regarding their consumption in the presence of price signals. The convergence of the proposed method can be dramatically accelerated, with a minimal loss of efficiency for which we also prove a theoretical upper bound. By adopting this approach, we guarantee the efficient and incentive-compatible VCG outcome, but also allow for a scalable, distributed implementation and a privacy-preserving communication protocol.

The proposed iterative mechanism can be implemented in configuration with a self-organized architecture that ensures privacy, while in the same time is able to exploit the aforementioned systems in order to further enhance its level of security (in contrast to the direct VCG mechanism).

5.4 Problem formulation and algorithmic solution

With respect to the system model (or else B2C flexibility market architecture) described above, we would like to facilitate the allocation of consumption reduction among the users so as to maximize social welfare. Social welfare is defined as the difference between the revenues that the aggregator receives from the operator for the consumption curtailment and the sum of the discomfort that this curtailment causes to its end users (or else end energy prosumers).

The difficulty in solving the above-mentioned social welfare maximization problem is that the discomfort function of each end user is not known, and thus, the problem is typically solved via dual decomposition in the related demand response literature. This approach, however, is not incentive compatible. In particular, the final allocation of the dual decomposition approach is identical to that obtained through the ascending English auction[11], which halts when supply equals demand. More specifically, in the system model described above and in case of an English auction, the aggregator would iteratively increase a per-unit reward asking the users their consumption reduction at each per-unit reward (auction query). At each

[11] For more details about the English auction, see here: https://en.wikipedia.org/wiki/English_auction

iteration, each user i responds with his/her preferred amount of reduction. The final price is commonly called the market-clearing price. However, truthful report may not be the best strategy for every user. This fact will be showcased via counter examples from simulations.

In order to facilitate the description of the proposed mechanism, we first present the Vickrey-Clarke-Groves[12] (VCG) mechanism, which is the unique mechanism that makes it a dominant strategy for each user, to act truthfully, i.e. in accordance with his/her real discomfort function. The VCG payment rule is the so called "Clarke pivot rule", which calculates a reward r_i equal to i's "externality". In other words, it rewards each user i with an amount equal to the difference that i's presence makes in the social welfare of other users.

In the direct VCG mechanism, end users are asked to declare their local functions to the aggregator. Thus, the efficient allocation that corresponds to the social welfare maximization problem can be calculated at the aggregator side. This raises important issues such as:

- Lack of privacy in case where users are reluctant to reveal local information (their discomfort function).
- Difficulty in implementation in cases where users are unable to express their preferences (i.e. discomfort function) in a closed form function.

Within FLEXGRID context, we propose a modification of Ausubel's Clinching auction [15], (which allows for a distributed implementation of VCG) designed to tackle these issues. In particular, we opt for an iterative auction that:

- Facilitates user bids via auction queries, thus making the proposed B2C flexibility market architecture more easily implementable in practice.
- Engages end users in the market and allocates consumption reduction gradually along the way, so that price discovery is facilitated on the end users' side.
- Protects end user's privacy via a properly designed communication protocol.

The Clinching Auction (CA) is a well-known ascending price auction (similar in fashion to English Auction) that halts when demand equals supply. However, in contrast to most auctions (including the English auction), allocation and rewards are not cleared exclusively at the final iteration. Rather, the goods (consumption reduction in our context) are progressively allocated as the auction proceeds and payments are also progressively built, while the auction design guarantees that the final allocation and final payments coincide with the ones obtained through VCG. Thus, both allocation efficiency and incentive compatibility are achieved, while the aforementioned privacy and implementation drawbacks of the direct-VCG mechanism are effectively addressed. The critical advantage of the Clinching auction is that it allocates different amounts of units at different rewards, and the units that a user clinches do not depend on his/her own bid, but only on the other users' bids.

The proposed B2C flexibility market architecture exploits Kademlia [16] in order to execute the auction in a distributed fashion. In this way, the aggregator does not have to learn the answers to the queries, which are instead acquired only by users in a distributed fashion. Thus, the proposed architecture acts as a substrate that offers a service over which participating users cooperate in order to protect their personal data from the aggregator.

[12] For more details: https://en.wikipedia.org/wiki/Vickrey%E2%80%93Clarke%E2%80%93Groves_auction

Each node (i.e., end user/energy consumer) is identified by a number (nodeID) in a specific virtual space. The nodeIDs do not serve only as identification, but they are also used by the Kademlia algorithm to store and locate values/data hashes (i.e., the answers to the aggregator queries). This process is realized through a peer to peer routing service (implemented in the network application layer) that Kademlia offers. Towards this end, participating nodes create and dynamically maintain routing tables in a bottom up organized way. In fact, the nodeID provides a direct map to these data hashes by storing information on where to obtain them.

5.5 Simulation setup and performance evaluation scenarios

We will test the performance of the proposed scheme using detailed appliance models taken from the literature and then use simulations to demonstrate the advantages of the proposed auction and verify its properties.

The first appliance model is taken from [1] and includes appliances that control the temperature of an environment, such as HVAC units. The room temperature evolves according to first order dynamics, and the discomfort for the end user is defined as the square difference between actual and desired temperatures.

The second appliance model represents temporally flexible loads (e.g., EVs) and is taken from [74]. The EV is plugged-in and has a total energy demand. The end user wants the EV to be charged as soon as possible and any delay would bring discomfort. This model accurately represents en-route charging EVs. During a FlexRequest, a user may choose to curtail some of the EV's load and shift charging to a later timeslot. This delayed charging comes with a discomfort.

The simulation setup will be a time horizon of 24 timeslots, with a duration of 15 minutes for each timeslot and for a setting of numerous (e.g. 50) users. A FlexRequest is simulated in some timeslots, especially at timeslots where there is a peak in the aggregated consumption.

The proposed scheme is compared to the direct-revelation VCG method (proposed in [9]), in terms of scalability with respect to the number of users. We expect that the proposed Modified Clinching Auction (MCA) will scale remarkably well to any number of users, since the algorithm's convergence time does not depend on the number of users. Moreover, the communication latency is defined as the total time overhead that the proposed distributed implementation introduces due to data network delays between any two data network nodes. As it is known theoretically, this latency increases logarithmically with the number of users. This assertion will be verified by simulations. Our goal is to demonstrate that the proposed scheme will be able to converge to the optimal solution within the order of a few minutes (or even seconds). This is very important in order to assess that the proposed scheme can be applicable for near-real-time demand response applications.

5.6 Summary of Key Performance Indicators (KPIs) to be measured

A mechanism is generally evaluated by: i) its performance in terms of social welfare, i.e. efficiency, ii) the tractability of the outcome, and iii) its incentive guarantees. The first two are commonly addressed in the literature and point to the allocation's efficiency and the mechanism's convergence time and consequent scalability. In contrast, the third requirement (that points to truthful participation of end users) is widely overlooked in the related demand response literature. In the few cases where truthfulness property is addressed, it comes with a sacrifice of practical implementability and users' privacy.

User strategies in games such as the one we described are subject to thorough study and discussion. Mechanism design theory classifies a mechanism's incentive guarantees with respect to how users are expected to act when participating in said mechanism. The strongest guarantee is called Dominant Strategy Incentive Compatibility (DSIC). We say that a mechanism is DSIC when it is at each user's best interest to truthfully implement his/her true preferences at any query, regardless of what other users do. A weaker guarantee is called Bayes-Nash Incentive Compatibility (BIC). A mechanism is BIC, when a user's best strategy is to act truthfully, if others also act truthfully. The proposed mechanism will be classified in terms of its incentive guarantees, while it will also be evaluated for a number of different scenarios. We will also compare our proposed scheme with the marginal cost pricing method [1] in terms of truthfulness.

Moreover, the efficiency of the proposed scheme will be evaluated in terms of the social welfare achieved, in comparison to the optimal social welfare. The optimal social welfare is the one that would be obtained if the aggregator had all the local information available and could apply direct control to the users' appliances. In other words, this requires a centralized B2C flexibility market architecture such as the one extensively described in chapter 3 of this report.

A major drawback of the direct VCG mechanism is that it requires each user to know and disclose his /her discomfort function to a central entity, e.g., the aggregator. The proposed Modified Clinching Auction (MCA) implements the VCG allocation and payments via an indirect mechanism. In this way, users are only required to respond to aggregator queries, instead of being required to communicate their discomfort function. This allows a distributed implementation of an efficient and truthful B2C flexibility market architecture. We will present a distributed communication protocol that preserves privacy while simultaneously ensuring an efficient allocation. We will evaluate the proposed (distributed) scheme in terms of convergence time and scalability, and we will compare it with the direct-revelation VCG method [9] in terms of scalability.

We will also investigate the effect that cheating has on the aggregator's profits, for the case where users act truthfully and for the case where they act according to what brings them the highest utility. We will thus investigate the impact on the the aggregator's profit loss due to various scenarios of end users' untruthfulness. Finally, we will compare our scheme with the marginal cost pricing method [1] in terms of aggregator's profits.

6 Automated Flexibility Aggregation Toolkit - AFAT

This chapter aims at describing the operation of the proposed Automated Flexibility Aggregation Toolkit (AFAT) and more specifically how the proposed FLEXGRID intelligence presented in chapters 3-5 will be integrated in AFAT. Moreover, this chapter's goal is to describe in a high-level of abstraction the structure of the graphical user interface (GUI) that the aggregator user will be able to visualize in FLEXGRID ATP.

So far, in FLEXGRID, we have done the following work with respect to the AFAT:

- A requirements' analysis work has taken place for both the AFAT S/W toolkit and the aggregator user (see more details in D2.1 [95]).
- An initial business and market analysis has been undertaken for AFAT including a SWOT analysis, description of AFAT as an exploitable commercial asset, etc. (see more details in D8.1 [96]).
- The internal AFAT S/W architecture has been described together with technical specifications and a draft data model to be followed regarding AFAT's algorithmic inputs/outputs (see more details in D2.2 [97]).

6.1 AFAT and aggregator user requirements' analysis

The aggregator user will be able to login the FLEXGRID ATP and after being authenticated by the platform, s/he will be redirected to the AFAT GUI (i.e. frontend) it has access to. From this frontend, the aggregator user will be able to visualize various information as well as configure and execute several algorithms. These algorithms will be running at the AFAT's backend, which will provide "black box" functionalities to the aggregator user. In other words, the aggregator user will be able to setup simulation scenarios, then push the respective "Run Algorithm" button and finally visualize the results in the ATP's GUI. In a nutshell, the AFAT's requirements are:

- AFAT's intelligence will be an open-source S/W and modular-by-design in order to be easily integrated as a module of a more complex S/W platform such as FLEXGRID ATP.
- AFAT will have a user-friendly GUI for the aggregator user in ATP and a backend system where all WP3 algorithms' intelligence will reside.
- AFAT will have a bi-directional API with the central FLEXGRID database in order to: i) acquire ("pull") input data required for algorithms' execution, and ii) send ("push") algorithms' output data to the database in order to be stored and be retrievable at any time in the future.
- AFAT will support end user (i.e. end energy prosumer) profiling, searching and recommendation functionalities.
- AFAT will be able to setup, operate and clear a novel B2C flexibility market (i.e. advanced interaction between the aggregator and all the end users).
- AFAT will have a bi-directional API with the core FLEXGRID ATP in order to: i) acquire related ("pull") data once a new FlexRequest is published in ATP, and ii) send ("push") the algorithmic results of the automated flexibility aggregation (i.e. FlexOffer,

dispatch per end user, etc.) to the ATP so that the aggregator user can visualize them and all the other ATP users are informed about them.

6.2 AFAT as an exploitable commercial asset

AFAT has been designed in a way that can be commercially exploitable as a standalone S/W toolkit, which can be integrated as a S/W "plug-in" in other larger S/W platforms developed by energy aggregator and progressive utility companies in the future. Within the FLEXGRID's context, AFAT will be integrated in the FLEXGRID S/W platform (ATP) and its operation will be tested via extensive lab experimentations and pilot tests within WP7. The main target groups of AFAT are:

- Individual researchers and research groups, who want to use AFAT for research and experimentation purposes.
- Aggregators (either independent companies or part of progressive utility companies or else ESPs) for business provisioning of new innovative FlexContracts with their end users being thus able to automatically compose optimal FlexOffers for their participation in high-end markets (e.g. day-ahead, balancing, etc.).
- Aggregator/Retailer companies for simulating advanced pricing schemes and market clearing mechanisms before releasing them in advanced B2C flexibility markets.

6.3 AFAT S/W architecture, interaction with other subsystems and algorithms' integration

In technical terms, the internal AFAT S/W architecture comprises of the following S/W modules, which will be developed within WP6:

- Web REST API for bi-directional data exchange between the central FLEXGRID database and the AFAT
- Web REST API for bi-directional data exchange between the core FLEXGRID ATP and the AFAT
- Data Acquisition Module
- Forecasting Engine
- Flexibility Aggregation Algorithm Module
- Retail Market Mechanisms Module
- Task Execution/Monitoring Module
- Internal Database

Regarding the first web REST API, one server-side REST API will be implemented at the central FLEXGRID database and one client-side REST API will be implemented at the AFAT side. Once a new AFAT algorithm needs to be executed, the Data Acquisition Module (client-side) will request for required input datasets in an appropriate data structure. Then, the server-side REST API will prepare/retrieve the requested datasets from the central database and will send them back to the AFAT's Data Acquisition Module (DAM). The final step will be for the DAM to forward the datasets to the appropriate Algorithm Module, so that the algorithm can run. Once the algorithm's execution has been finished, its results/output datasets will be stored in AFAT's internal database.

As of the ATP-AFAT web REST API, one server-side REST API will be implemented at the AFAT side and one client-side REST API will be implemented at the core FLEXGRID ATP side. The aggregator user will utilize the respective ATP's GUI in order to visualize all AFAT-related information (i.e. visualize the profiles of all its end users, clusterings of end users, algorithmic results, etc.). Especially for the execution of a specific algorithm (i.e. simulation), the aggregator will be able to set various input parameters in a user-friendly GUI and then press the "execute algorithm" button. Subsequently, the ATP REST client will automatically construct the declared datasets in a fine-grained JSON format and send them to the AFAT REST API server. The latter will forward these input datasets to the appropriate module in order for a respective algorithm to be executed. Once the algorithm's execution has been finished, its results/output datasets will be stored in AFAT's internal database and will also be available upon request for the aggregator user to visualize them and further process them. The ATP REST client will also forward a FlexRequest to the AFAT once this is generated and published in the ATP. Subsequently, the AFAT REST API server will receive this FlexRequest and use as input data for the execution of a flexibility aggregation algorithm.

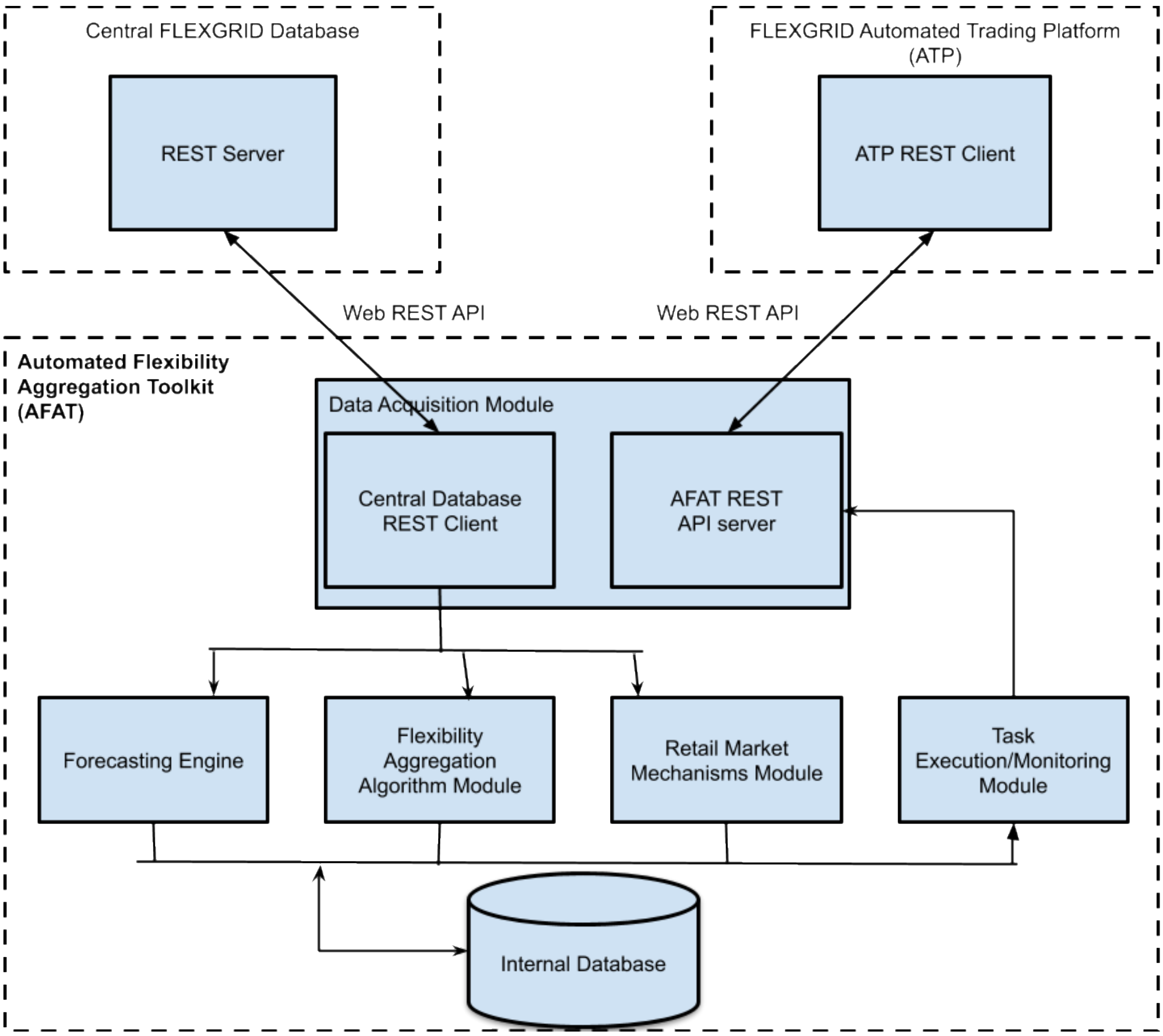

Figure 6: The Automated Flexibility Aggregation Toolkit (AFAT) internal architecture (taken from [97])

The “Forecasting Engine” module will integrate the market price and PV generation forecasting algorithms that are being developed by UCY. Extensive technical details regarding the basic system model that is followed, basic algorithmic solutions to be adopted and KPIs to be measured are provided in chapter 2 of D4.1. It should be noted that this forecasting engine module is the same with the one residing at the FST’s internal S/W architecture. The only difference is that in AFAT, it is used for facilitating an independent aggregator’s business, while in FST, it is used for an ESP’s business.

The “Flexibility Aggregation Algorithm Module” will integrate the respective mathematical models and algorithms that have been extensively described in chapters 3 and 4 above. For example, for a given FlexRequest generated by the ATP, the AFAT will run a flexibility aggregation algorithm whose result will the optimal dispatch schedule for each participating end user (cf. chapter 3 for more details). Another example is that the aggregator wants to automatically create an optimal FlexOffer by orchestrating all distributed and heterogeneous flexibility assets in a way that best represents its portfolio (i.e. quantity/price pairs per timeslot) for a given future timeframe (cf. chapter 4 for more details).

The “Retail Market Mechanisms Module” will integrate the respective mathematical models and algorithms that have been extensively described in chapter 5 above. With the term “retail market”, we actually mean a novel B2C flexibility market organized and operated by the aggregator, which enables dynamic FlexContracts and competition among the end users instead of rather static FlexContracts (rewarding both availability and activation at a fixed price and for a given fixed times of activation) that are assumed in the centralized optimization research problem analyzed in chapter 3. Hence, decentralized optimization approaches will be adopted facilitating advanced pricing models and auction-based mechanisms (cf. chapter 5 for more details).

The “Task Execution/Monitoring Module” will be responsible for the execution and monitoring of the processing tasks (i.e. algorithmic runs) that have been submitted for execution in AFAT. This module will allow for submitting, canceling, and viewing the status of each submitted processing task by the aggregator user. It may also send notifications when there is a status update. Hence, the aggregator user will be able to easily monitor the progress of each processing task through its user-friendly GUI. This is important because many of the AFAT algorithms are expected to last for a relatively long timeframe (e.g. several minutes or even hours depending on the computational complexity and volume of input data).

Note: In chapter 7 of D2.2 [97], there is an extensive list of the required input and output data per algorithm category that will be created and exchanged among the above-mentioned S/W modules. The final version of the data models will be developed within Task 6.1 and will be officially delivered in Month 18 through D6.1.

6.4 Draft structure of the Aggregator’s Graphical User Interface (GUI)

This section provides a tentative list of web pages that the aggregator user will be able to visualize and use. As already stated in D2.2 [97], the WISECOOP S/W infrastructure developed by ETRA within the H2020 WISEGRID energy flagship project[13] will be used as a S/W substrate upon which additional novel FLEXGRID intelligence (cf. AFAT) will be integrated. Moreover, UI ideas from H2020 SOCIALENERGY RABIT[14] [98] will be taken into account. In a nutshell, the aggregator user will be able to visualize the following web pages:

- AFAT dashboard
- Prosumer monitoring
- Prosumer clusters
- Reports/Recommendations
- FlexContracts and Prosumer Registration
- Manage a FlexRequest
- Create a FlexOffer
- Manage a B2C flexibility market

The "AFAT dashboard" web page will contain general information illustrating a selection of the most important KPIs for the aggregator user. For example, these KPIs will be: i) list of most recent FlexRequests that have been responded by the aggregator, ii) list of most recent FlexOffers that the aggregator has submitted in ATP, iii) sum of aggregator's revenues, expenses and profits for a given timeframe, iv) overall flexibility units (MWh) that have been delivered to the system by the aggregator, v) overall aggregator's contribution in reducing CO2 emissions, vi) recent portfolio's/per prosumer type consumption and production.

The "Prosumer Monitoring" web page will facilitate the visualization of all end energy prosumers' consumption, production and storage data. The data can be both historical and real-time. Historical data will mainly be used for the algorithmic executions and validation of mathematical models and algorithms, while real-time data for the testing and validation of FLEXGRID platform within WP7 context.

In the "Prosumer Clusters" web page, the aggregator user will be able to visualize aggregated energy prosumption profiles from multiple end energy prosumers, who may have a common characteristic (e.g. all residential prosumers or only those who reside in a specific location, or only those whose energy profile/pattern is similar). This page will also offer filtering functionalities in order to easily identify a subset of prosumers, while each cluster may be also used for broadcasting a recommendation message to multiple prosumers.

The "Reports/Recommendations" web page will be mainly used in to send automatic messages (i.e. e-mails) to a cluster of energy prosumers, which has been created in the above-mentioned page "Prosumer Clusters". For example, after running specific retail pricing algorithm, the aggregator will be able to recommend more beneficial FlexContracts to a subset of energy prosumers, who seem to have greater potential for flexibility service provisioning.

In the "FlexContracts and Prosumer registration" web page, the aggregator can add new end users with all their personal details (i.e. location, category, type of FlexContract, supplier id,

[13] https://www.wisegrid.eu/project-tools

[14] SOCIALENERGY RABIT is S/W tool that has been developed in the context of H2020-GA-731767 SOCIALENERGY project coordinated by ICCS.

etc.). Moreover, in this web page, the aggregator can set up several types of FlexContract and allocate each one of them to an end prosumer based on the latter's preferences. The FlexContracts will be editable and can be changed by the aggregator user if the interested end prosumer has previously agreed.

The "Manage a FlexRequest" web page functionalities are closely related to the research problem that was described in chapter 3. Assuming an (emulated) online operation of FLEXGRID ATP, a FlexRequest will be published in the ATP and in real-time the AFAT will redirect it to the "Flexibility Aggregation Algorithm Module". After the algorithm's execution, the aggregator user will be able to visualize: i) the optimal energy prosumption schedules for each participating end energy prosumer (i.e. setpoints for a given time horizon of the specific FlexRequest), ii) aggregated users' welfare, iii) aggregator's revenues and expenses, iv) aggregator's profits. The same process can be followed for an offline operation, meaning that the aggregator user will be able to setup a simulation scenario by configuring manually several input parameters. Hence, the aggregator may run exhaustive "what-if" simulation scenarios in order to deeply comprehend ways to optimally respond to future FlexRequests increasing thus its profits and reward its end prosumers more effectively. For example, the aggregator may "play around" with various types of FlexContracts, various types of FlexRequests, different sets of participating end users, different sequence of FlexRequests, etc.

The "Create a FlexOffer" web page functionalities are closely related to the research problem that was described in chapter 4. Assuming an (emulated) online operation of FLEXGRID ATP, the AFAT will be able to generate FlexOffers for a given future timeframe and submit them in ATP. The FlexOffer will represent the aggregated flexibility of the portfolio in the best possible way ensuring that the aggregator's profits can be maximized without risking that the respective schedule cannot be met by the participating end users given the constraints imposed by the various FlexContracts. Moreover, the aggregator will be able to see if the FlexOffer has been accepted or rejected and in the former case, the schedules per participating end user will need to be actuated. The same process can be followed for an offline algorithmic operation, meaning that the aggregator user will be able to setup a simulation scenario by configuring manually several input parameters. This way, the aggregator user will be able to test and validate its portfolio (i.e. in terms of reliability, availability, network constraints or other possible malfunctions) before issuing a FlexOffer in the real ATP.

Finally, via the "Manage a B2C Flexibility Market" web page, the aggregator user will be able to setup simulation scenarios in order to identify interesting business cases for operating a novel B2C flexibility market. Due to the fact that a B2C flexibility market does not exist (mainly because of the fact that advanced and intelligent agents at the home energy management system are required), we will assume an offline algorithmic operation. This web page's functionalities are closely related to the research problem that was described in chapter 5.

7 Conclusions

In the following months, FLEXGRID consortium will progress the current work presented in this report and implement the algorithms and methods of the UCSs of HLUC_04 and the design of AFAT. All three tasks of WP3 are under progress. More analytically:

- The automated composition and optimal operation of flexibility architecture is described, with the architecture of advanced DFA markets and P2P trading having reached a mature stage. The necessary datasets, performance evaluation scenarios and KPIs have been described in this deliverable. Bidding processes, allocation rules and communication rules are being developed. The problem formulation and the algorithmic solutions have been presented. Partners are working towards the final mathematical models and the datasets in order to have the first outputs of the optimization problems.
- From the following month, M13, all partners will start working towards the implementation and integration of each individual subsystem into the single modular-by-design FLEXGRID S/W platform.

In the figure below, the timeline of WP3 is illustrated. Milestone #4 has been achieved with this deliverable, while two milestones remain for months #18 and #26 with the submission of deliverables D3.2 and D3.3 respectively.

Figure 7: Current FLEXGRID project's WP3 timeline schedule (MS 4 has been accomplished)

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