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

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Final Version of Advanced Energy Service Providers' and Renewable Energy Service Providers' Business Models

Deliverable D4.3

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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
AC	Alternate Current
AFAT	Automated Flexibility Aggregation Toolkit
AI	Artificial Intelligence
ANN	Artificial Neural Network
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
BM	Balancing Market
BP	Back Propagation
BRNN	Bayesian Regularization Neural Network
BRP	Balance Responsible Party
BSU	Battery Storage Unit
CA	Clinching Auction
CAPEX	Capital Expenditure
CV	Cross Validation
CES	Cloud Energy Storage
DA-DLFM	Day-Ahead Distribution Level Flexibility Market
DA-EM	Day-Ahead Energy Market
DAM	Day-Ahead Energy Market

DA-RM	Day-Ahead Reserve Market
DC	Direct Current
DER	Distributed Energy Resource
DFA	Distributed Flexibility Asset
DLFM	Distribution Level Flexibility Market
DN	Distribution
DNN	Deep Neural Network
DQR	Data Quality Routine
DR	Demand Response
DSIC	Dominant-Strategy-Incentive-Compatibility
DSM	Demand Side Management
DSO/TSO	Distribution/Transmission System Operator
ECC	Energy Consumption Curve
ELM	Extreme Learning Machine
ESP	Energy Service Provider
ESS	Energy Storage System
EV	Electric Vehicle
FMO	Flexibility Market Operator
FST	FlexSupplier's Toolkit
GHI	Global Horizontal Irradiance
GUI	Graphical User Interface
HVAC	Heating, Ventilation and Air Conditioning
ICT	Information and Communication Technology
IDM	Intraday Energy Market
IEA	International Energy Agency
KPI	Key Performance Indicator
MAPE	Mean Absolute Percentage Error
MCA	Modified Clinching Auction
MDP	Markov Decision Process
MEA	Mean Absolute Error
MFAL	Market Forecast Accuracy Level
MGO	MicroGrid Operator
ML	Machine Learning
MLP	Multi-Layer Perceptron
MM	Market Mechanism
nRMSE	normalized RMSE
NWP	Numerical Weather Prediction

OPEX	Operating Expenses
OPF	Optimal Power Flow
PV	Photovoltaic
PVPS	PV Power System
RES	Renewable Energy Sources
REST API	RESTful Application Programming Interface
RF	Random Forest
RMSE	Root Mean Square Error
SMO	Storage Market Operator
SOCP	Second-Order Cone Programming
S/W	Software
SWOT	Strengths Weaknesses Opportunities Threats
TCL	Thermostatically Controlled Loads
TN	Transmission
TOU	Time of Use
VCG	Vickrey-Clarke-Groves
VESS	Virtual Energy Storage System
VPP	Virtual Power Plant
WEMM	Wholesale Electricity Market Module
WRF	Weather Research and Forecasting

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Document History

This deliverable includes the final version of the mathematical models, research problem formulations, algorithms and performance evaluation results for the advanced ESP and RESP Business Models.

Table 1: Document History Summary

Revision Date	File version	Summary of Changes
08/07/2021	v0.1	Draft ToC circulated within all consortium partners
21/07/2021	v0.2	All partners commented on the draft ToC structure
29/10/2021	v0.5	UCY sent their contributions
08/11/2021	v0.6	ICCS sent their contributions
16/11/2021	v0.7	UNIZG-FER sent integrated D4.3 draft to DTU for internal review
24/11/2021	v0.75	DTU reviewed the document and made comments
29/11/2021	v0.9	All the comments have been addressed and the pre-final version was sent to the coordinator
30/11/2021	Final	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 WP4 subsystems and their interactions as well as the respective technical specifications emphasizing on the detailed description of WP4 research problems. The focus of this document is FLEXGRID High Level Use Case #2 (HLUC_02), which primarily focuses on the profit-oriented Energy Service Provider (ESP) and the services it may obtain using the FLEXGRID ATP platform, more specifically the FlexSupplier's Toolkit (FST).

Six Use Case Scenarios (UCSs) are presented for the development of innovative market operation models and business models that offer to ESPs the easy planning and operation of their assets according to the innovative FLEXGRID energy market architecture. The respective algorithms (i.e. algorithms from UCSs 2.1, 2.2 and 2.3) will be integrated in a S/W toolkit entitled FlexSupplier's Toolkit (FST), which will dynamically interact with the core FLEXGRID ATP.

Chapter 1 brings an introduction to this report summarizing the scope and purpose of the document. More specifically, it provides a description of High Level Use Case #2 (HLUC_02) and the interaction with the FLEXGRID system. It summarizes the research innovations, the research impact on energy service provider's (ESP) business models, including policy recommendations and lessons learnt.

Chapters 2-7 follow a similar structure and extend the work presented in the respective chapters in previous D4.1 (delivered in M12) and D4.2 (delivered bin M18). They are structured in such a manner to encompass the following points:

- A summary of FLEXGRID research results so far
- System model
- Problem formulation
- Algorithmic solution
- Simulation setup and performance evaluation results
- Concluding remarks and lessons learned

Chapter 2 deals with the topic of advanced forecasting services both to predict market prices and FlexAssets' state in the future. The main contributions are related to the: i) PV generation forecasting and ii) market price forecasting. Topics such as (i) have more importance than ever as the stability of the electricity grid faces new challenges due to the variable and intermittent nature of generated power that is dependent on the weather conditions. Combining the WP3 and WP4 contributions, a methodology for both day-ahead and intra-day PV generation is proposed together with a model based on the Artificial Neural Network (ANN). Market price forecasting functionality, as part of the HLUC04_UCS04 is provided to the ESP and aggregator actors and is based on the Extreme Learning Machine (ELM) methodology.

In Chapter 3, the research problem of the FLEXGRID UCS2.1 is presented. The emphasis is on deriving optimal scheduling algorithms for the profit-oriented ESP user. In a modern electricity system, the ESP may participate in many various markets and have many FlexAssets under different contractual arrangements. Sub-optimal business strategies may result in loss of the market share for the respective ESP and consequently less profit. Hence, OPEX minimization problem based on the proposed optimal scheduling model and algorithm may boost ESP's profits and create comparative advantage over the competition. Moreover, tools that enable business sustainability in the high RES penetration scenarios may even accelerate the whole energy transition process. As part of the whole FLEXGRID project concept, a novel Distribution Level Flexibility Market (DLFM) is considered and incorporated in the model. More specifically, Reactive and Proactive-DLFM architectures are considered, as the first version may be easily added to the current market paradigm without any major modifications, while the latter offers more incentivization in terms of more monetary benefits for the ESP.

Chapter 4 presents the work performed under the FLEXGRID UCS 2.2. The primary objective is to utilize a novel siting and sizing algorithm in such manner to minimize ESP's investment costs (CAPEX) in RES and FlexAssets. The holistic network-aware approach takes into consideration various electricity markets, network topology and constraints or, at least, reduced network topology knowledge - DSO's geographical zone approach as in the NODES flexibility marketplace paradigm, detailed study of various battery types (their characteristics such as charging/discharging efficiency, etc.), RES generation (weather), consumption and market price forecasts. Such an approach should enable efficient exploitation of available instruments to ensure reliable energy supply with the lowest possible CAPEX. The single-level optimization problem assumes the ESP as a price-taker that may also be the same entity as DSO, or at least have all the vital network topology information for the algorithm to run properly.

Chapter 5 presents the research problem of the FLEXGRID UCS 2.3. It analyses a profit-seeker ESP, who owns a set of Battery Storage Units (BSUs) located at various nodes of a distribution network. In order to maximize its stacked revenues, the ESP may co-optimize its participation in several energy markets, including the proposed Distribution Level Flexibility Market governed by the respective Flexibility Market Operator (FMO), and dynamically optimize its bidding strategy. In more detail, it exploits market price forecasts, energy prosumption forecasts and information on the underlying network topology in order to derive its optimal scheduling and bidding strategy towards maximizing its operating profits. To formulate the ESP's decision process, we propose a bi-level model, where the lower-level problems represent the clearing processes of the Reserve and the Flexibility Markets, in which the ESP participates strategically (i.e. as a price maker).

Chapter 6 consists of the efforts made as part of the research problem of FLEXGRID UCS 2.4. Advanced models and algorithms are developed that factorize three main requirements that modern ESP companies need to adopt in order to efficiently interact with the various market and network dynamics that high RES penetration brings into the system, namely: 1) adopt imperfect market context - aware bidding strategies to maximize their profits, 2) respect the underlying network constraints, and 3) make decisions about the optimal mix of their heterogeneous flexibility assets as well as their optimal sizing, siting and operation. The main purpose is to schedule Energy Storage Systems (ESSs) and Demand Side Management (DSM) systems optimally and in an integrated way to maximize a price maker ESP's profits. In this UCS, we consider that the ESP is aware of the network topology data and can thus participate in energy markets in a network-aware manner (i.e. by not causing network infeasibility problems to the DSO).

Chapter 7 considers the work done under the FLEXGRID research problem UCS 2.6. Here, we focus on large FlexAsset owners, who are willing to lease their storage capacity to several interested parties. The main interaction is between a large FlexAsset owner that wants to lease its storage capacity(/power) and a user willing to outsource their energy storage system needs by procuring them from the mentioned FlexAsset owner. Such business model may generate income to the FlexAsset owner simply by leasing its storage capacity, while various market participants may generate profit (or lower costs), increase safety & reliability and postpone capital intensive actions using leased storage capacity that they do not own. Variation from this approach is a concept where storage market operator (SMO) plays the role of an intermediate like platforms such as Airbnb, Booking, Uber and other similar business models. SMO does not own (at least it doesn't have to) any storage facilities, but it connects supply with demand and guarantees both sides of the deal that certain rules will always be respected. So, the operator aggregates virtual battery storage facility composed of many distributed storage systems with different characteristics.

Finally, in Chapter 8, we describe the integration of the research work of WP4 within the FST and FLEXGRID ATP (WP6), the validation and implementation in pilot sites (WP7) and the relation/interaction of the aggregator within the WP8 business models, values propositions, and the exploitation plan.

1 Introduction

1.1 Description of High Level Use Case #2 and interaction with FLEXGRID system as a whole

In the High Level Use Case (HLUC) #2 the focus is on the development of advanced flexibility management services for the profit-oriented Energy Service Providers (ESPs). An ESP is, per definition in D2.1[1] a profit-oriented company, which may enter into contractual arrangements with various types of flexibility assets (e.g. DSM, RES, storage). Services provided via FLEXGRID ATP, or more specifically – FlexSupplier's Toolkit (FST), to the respective ESP, are intended to help utilizing FlexAssets in an optimal manner. These service include advanced forecast methods both for market prices and RES generation (emphasize on PV), together with models and algorithms to optimize ESP's market behavior in a holistic way (e.g. via optimal scheduling, bidding, siting and sizing models and algorithms). Deliverables D2.1 and D2.2 documented respective Use Case Scenarios (UCSs), which encompass the above-mentioned features.

The focus of interest in the HLUC #2 is the ESP actor, its participation in various markets and its interaction with DSOs/TSOs and BRPs. Different formulations of Distribution Level Flexibility Markets are considered and characteristics of each analyzed and commented for different use cases. Although participation of ESPs in DLFMs is closely analyzed, it is important to mention that ESP is not constrained only on providing flexibility services, but it may participate in all existing markets (e.g. day-ahead energy market, reserve market, balancing market, etc.).

In the previous deliverables (D4.1 and D4.2), six research problems have been clearly defined. Four of them are an integral part of WP4 efforts, whereas one research problem (RES and market forecasting) is also analyzed as part of the WP3 efforts. In D4.1, a high-level description of the six research problems has been presented, including a survey of related works from the international literature. Furthermore, FLEXGRID's research contributions have been clearly defined and hints about the problem formulation, algorithmic solution, datasets to be used for the system-level simulations and most important key performance indicators (KPIs) have been presented. D4.2 further elaborated on the work of D4.1, close-to- final version of mathematical modeling and proposed algorithms were presented. Where possible, initial performance evaluation results were also presented.

This deliverable further extends the work done in the previous deliverables (D4.1 and D4.2) with final mathematical models and the presentation of the performance evaluation results.

[1] https://flexgrid-project.eu/assets/deliverables/FLEXGRID_D2.1_v1.0_31012020.pdf

1.2 Summary of FLEXGRID's research innovations

Following the work done in previous deliverables, four research problems directly focused on ESP were identified and one combined WP3 and WP4 work efforts. For each of these problems, the approach was similar. The process consisted of formulating mathematical models and creating appropriate tools to propose new and enhance existing ESP business models. The research problems are following:

1. ESP exploits FLEXGRID's advanced forecasting services to predict market prices and FlexAssets' state and curves in the future (cf. UCS 4.4)
2. The ESP user wants to minimize its operational expenses (OPEX) by optimally scheduling the consumption of end users, production of RES and storage assets (cf. UCS 2.1)
3. The ESP user wants to minimize its capital expenditures (CAPEX) by making optimal investments (i.e. optimal siting and sizing) on RES and FlexAssets (cf. UCS 2.2)
4. The ESP user wants to create an optimal FlexOffer for simultaneous participation in multiple markets to maximize its business profits (cf. UCS 2.3)
5. Market-aware and network-aware bidding policies to optimally manage a virtual FlexAssets' portfolio of an ESP (cf. UCS 2.4)
6. Independent large FlexAsset Owner leases storage for several purposes to several market stakeholders (cf. UCS 2.6)

Chapters 2-7 focus on each of the above-mentioned research problems, respectively. The first research topic, which focuses on advanced forecasting services to predict market prices and PV output in the future, is combined work effort from WP3 and WP4, while other research problems are entirely WP4 related. Research problem in chapter 3 derives optimal scheduling algorithm to minimize ESP's OPEX, whereas the next chapter focuses on minimizing ESP's CAPEX using novel siting and sizing algorithm. Chapter 5 presents algorithms developed to maximize ESP's stacked revenues; next chapter further elaborates on work presented in D4.2 by applying the proposed mathematical model and algorithm for a MicroGrid Operator's (MGO) business case. Chapter 7 concludes WP4 related research problems considering large FlexAsset owners who are willing to lease their storage capacity to several interested parties. Each of the above-mentioned chapters are similarly structured to encompass:

- A summary of FLEXGRID research results so far
- System model
- Problem formulation
- Simulation setup and performance evaluation results
- Concluding remarks and lessons learned

1.3 Summary of FLEXGRID's research impact on today and future ESP's business

The work of WP4 focuses on the scientific excellence of the proposed FLEXGRID services (identified open research items) at TRL3. The most important WP4 scientific results are adapted in order be able to serve the business needs of an aggregator. Thus, in WP6, our focus is on FLEXGRID's research impact on today and future ESP's business by demonstrating WP4 from the short-listed UCSs (2.1, 2.2, 2.3) intelligence in the FLEXGRID ATP (i.e. TRL 5).

More specifically, FST's frontend (GUI) will be comprised of three basic tabs, namely:

- ESP's OPEX minimization (UCS 2.1)
- ESP's CAPEX minimization (UCS 2.2)
- ESP's profit maximization (UCS 2.3)

Following up the FST's frontend services, three main WP4 algorithms are being integrated in FST's backend, namely:

- A scheduling algorithm enables the ESP user to reduce operational expenses, while respecting given constraints. The algorithm determines the optimal operation schedule for the FlexAssets in the ESP's portfolio. The proposed solution is described in detail in chapter 3 (cf. UCS 2.1).
- A siting and sizing algorithm for the potential new FlexAssets in a least capital cost manner, while meeting some goal such as e.g. 5% OPEX reduction. The proposed solution is described in detail in chapter 4 (cf. UCS 2.2).
- An algorithm that generates an optimal set of energy and FlexOffers for simultaneous participation in multiple markets to maximize ESP's business revenues. The proposed solution is described in detail in chapter 5 (cf. UCS 2.3).
-

The table below summarizes how the WP4 research results (TRL 3) will be further exploited in WPs #6 and #8.

FST GUI (WP6)	**Mode of operation**	**Business goal (WP8)**
ESP's OPEX minimization	Online	Assume that the day-ahead market (DAM) dispatch is given and should be respected by the ESP. For an issued FlexRequest by DSO/TSO expected to be met by the respective ESP, a new schedule is calculated.
	Offline	The ESP user runs various "what-if" simulation scenarios assuming various FlexRequests and FlexAsset portfolios.
ESP's CAPEX minimization	Offline	The ESP user runs various "what-if" simulation scenarios assuming various mixes of FlexRequests and FlexAsset portfolios. ESP assumes a given OPEX reduction target (e.g. 5%) and tries to find the minimum CAPEX to meet this target.
ESP's profit maximization	Online	The ESP user has the initiative. It takes market price forecasting data for 4 markets (i.e. day-ahead, reserve, DLFM, balancing) and calculates 4 optimal energy and FlexOffers to submit in ATP.
	Offline	The ESP user runs various "what-if" simulation scenarios via running a stacked revenue maximization algorithm to identify how it can achieve maximum expected profits.

1.4 Summary of FLEXGRID policy recommendations and lessons learned

The research work of WP4 proposes novel business models for advanced ESPs and RESPs. The special emphasis has been given to x-DLFM architectures and, more specifically, strategies for ESPs to benefit from various potential DLFM versions; hence the operation of an online flexibility marketplace (i.e. FLEXGRID ATP) is assumed. The ESP may use the set of algorithms developed as part of the WP4 work efforts to manage its FlexAssets, optimally participate in various markets and consequently reduce its expenses (both CAPEX and OPEX). Some of the features may be used both online and offline, and some only offline with predefined scenarios, but all serve the respective ESP as a tool to analyse different possible decisions and formulate optimal business strategy taking in mind all necessary constraints and conditions. Based on the results and the multiple extensions of the research of WP4, policy and regulation makers can extend and formulate new strategies so that the respective ESPs and RESPs may successfully participate in future electricity market structures and consequently facilitate future high RES penetration scenarios and EU's smooth energy transition within the next decades. For more details about specific policy recommendations and lessons learned, the reader can follow the respective tables at the end of each chapter below.

2 PV Production and Market Price Forecasting (UCS 4.4)

2.1 PV Production Forecasting

FLEXGRID's research contribution services includes an accurate PV generation forecasting to ESPs/aggregators. ESPs/aggregators will be provided with forecasting services by aggregating their end-users' PV generation (both day-ahead and intra-day – predominantly from PV systems) and consider the other available assets such as battery storage.

Based on the previous deliverable D4.1 and D4.2 [1], [2] respectively, the FLEXGRID's PV generation forecasting services are located at the Automated Flexibility Aggregation Toolkit (AFAT) and FlexSupplier's Toolkit (FST). Succeeding the modular-by-design nature of FLEXGRID S/W architecture, the advanced forecasting algorithms are executed iteratively in the forecasting engine, while well-designed web APIs will provide:

i. the input parameters and data for the execution of algorithms;
ii. the output parameters that will be sent to the FLEXGRID ATP and then visualized by the ESP/aggregator users.

2.1.1 Introduction

Within the previous deliverable D4.2 [2], a short-term (hour-ahead) and medium-term (day-ahead) PV generation forecasting methodology was described based on a non-parametric ANN model. The ANN model was optimized according to the input and output parameters. To achieve accurate and efficient short-term and medium-term forecasting, three phases were followed, namely:

i. <u>Training:</u> For the training phase of the day-ahead PV generation forecast, historical data of the reference systems were used (P_{DC}). Furthermore, Numerical Weather Prediction (
ii. NWP) data were employed in order to evaluate the actual forecasting performance of the developed methodology. The NWP data were derived using the Weather Research and Forecasting (WRF) model, which is a mesoscale model designed for atmospheric research and operational forecasting applications. More specifically, the input parameters acquired from the NWP includes the global horizontal irradiance (*GHI*) as well as the ambient temperature (T_{amb}). Also, to improve the accuracy of the ML forecasting model, the elevation angle of the sun (α) and the azimuth of the sun (ϕ_s) are calculated using solar position algorithms and utilized to address the angular response of the PV systems.
iii. <u>Validation:</u> During this phase, the hyperparameters of the ML models are being optimized through a series of statistical and empirical approaches. The optimization phase is using the Early Stopping approach to avoid overfitting when the hyperparameters were not exhibiting any further improvements (in some cases declination might be demonstrated).
iv. <u>Testing:</u> During the testing phase, the forecasting accuracy of the ML model was assessed.

Figure 1 demonstrates the aforementioned procedure as described in [3], [4], too.

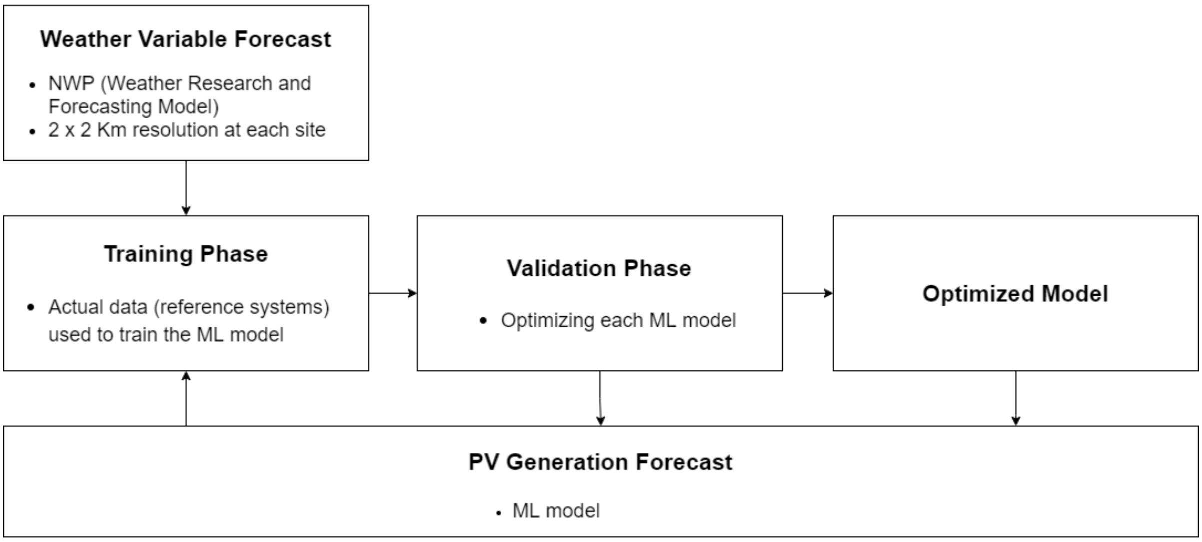


Figure 1 Flow chart of the day-ahead PV generation forecasting model: Overview

2.1.2 Extensive simulation results

The forecasting methodology used for UCS 4.4 is based on a Bayesian Regularized Neural Network (BRNN), while a sequence of training and validation stages was performed by varying the input parameters (features), samples used and architectural parameters (hyperparameters) of the devised machine learning models in order to construct the optimally performing ANN. Bayesian inference, L2 regularisation, and stochastic gradient descent were utilised along with the logistic sigmoid as activation function for each node. A detailed description of the specific stages followed to develop the PV production forecasting methodology was already provided in deliverables D4.1 and D4.2 [1], [2].

Summarizing the D4.1, for accurate day-ahead and hour-ahead PV generation forecast, high-quality historical data are needed. The more the forecasting model is trained with historical data, the more accurate the result will be. The input datasets include the historical observed PV power data (P_{dc}) and the historical NWP data; Ambient Temperature (T_{amb}), Global Plane of Array Irradiance (G_{poa}) or Global Horizontal Irradiance (*GHI*) of the same period are mandatory for the training and testing phase of the ANN model. Additionally, for the simulations, PV system coordinates will be also used to calculate the α, φ_{Ss}, sunrise and sunset time. Several predefined metrics are assessed for the forecasting performance accuracy. The metrics commonly used in PV production forecasting applications include the:

- Mean absolute error (MAE)
- Mean absolute percentage error (MAPE)
- Root mean square error (RMSE)
- Normalised root mean square error (nRMSE)

For the respective simulations, a test set period of 200 days in hourly intervals were used. Figure 2 shows the forecasting accuracy performance of the ANN model, evaluated by employing the daily nRMSE over a test set period of 200days. In Figure 2, a comparison between the ANN forecasting model without data quality routines (DQRs) and the ANN forecasting model with DQRs is presented. Specifically, the PV forecasting model without DQRs demonstrated an nRMSE of 11%, while the nRMSE of the PV forecasting model with DQRs was 9% (data points at solar irradiance levels <100W/m2 were filtered out). It is worth mentioning that the correction of the input data before the training phase of the ANN model can bring more accurate results. In Figure 2, a 2% decrease in the average nRMSE was noticed after correction of the input data.

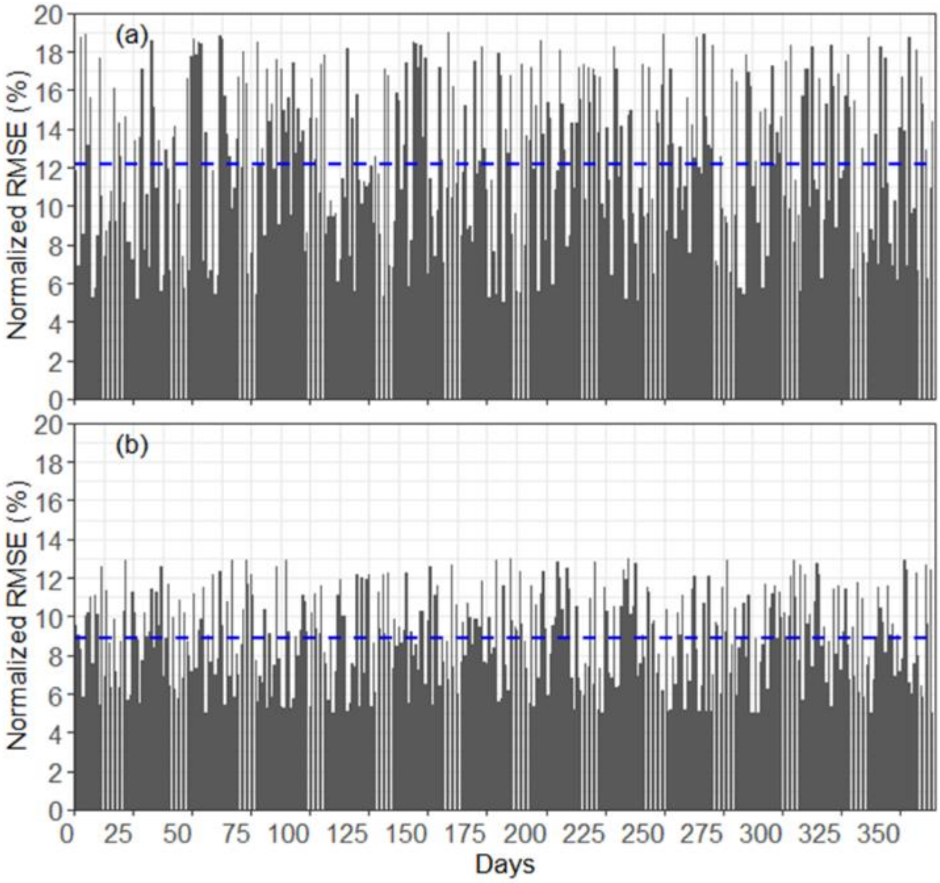


Figure 2 Daily nRMSE of: (a) Forecasting model without DQRs and (b) Forecasting model with DQRs. The blue dashed line of both figures demonstrates the average nRMSE.

Figure 3 shows the daily *MAPE* obtained when the optimal ANN day-ahead PV power production ensemble forecasting model with post-processing correction was applied to the test set period. The overall *MAPE* obtained was 4.7% (data points at solar irradiance levels <100 W/m^2 were filtered out).

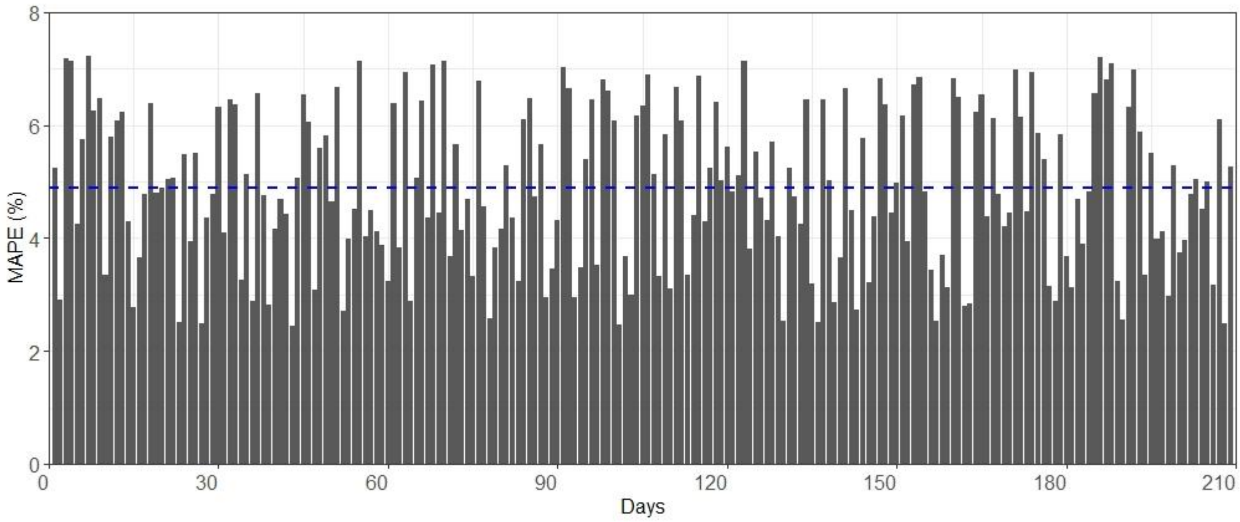


Figure 3 Day-ahead PV power production forecasting accuracy given by the daily MAPE when applying the optimal ANN day-ahead PV power production ensemble forecasting model with post-processing correction, over the test set evaluation period (210 days). The blue dashed line demonstrates the overall mean absolute percentage error (MAPE) at 4.7%.

Additionally, the scatter plot in Figure 4 demonstrates the forecasted and observed power output variation of the models at different in-plane solar irradiance levels. As shown in Figure 4, the obtained R^2 value for the reference model was 0.98 exhibiting a high linear correlation. This variation is more evident and influential at high in-plane solar irradiance conditions > 600 W/m^2. R^2 measures the quantity of variation in the dependent parameter that can be attributed to the independent parameter. R^2 is a value between 0 and 1, where 0 indicates weak fit while 1 indicates perfect fit.

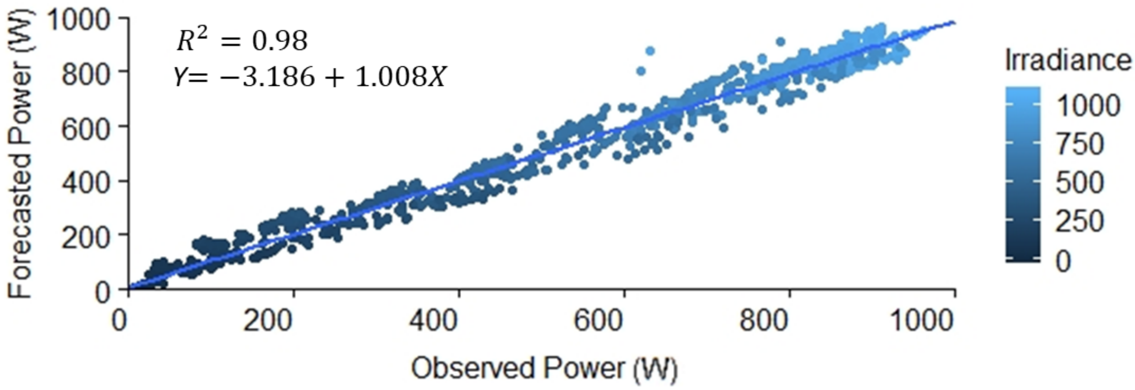


Figure 4 Scatter plot of forecasted and observed Power at different irradiance levels

Finally, to ensure the methodology's robustness to the K-fold cross validation (CV), the acquired dataset was separated into 8 folds of randomly selected data. At each evaluation CV round, the optimal BRNN forecasting model was trained with seven training set folds and tested against the remaining testing set fold. The process was finalized when all folds have been exploited as testing folds as shown in Figure 5.

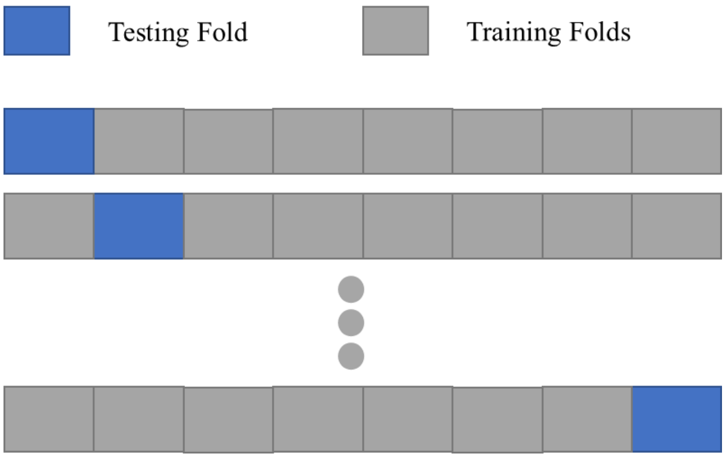


Figure 5 K-fold CV technique to investigate the robustness of the optimal BRNN forecasting model

Figure 6 shows the daily *nRMSE* results of the K-fold CV technique applied to the optimal BRNN forecasting reference model that ranged from 3.46% to 4.78%, with an average of 4.01% and standard deviation of 0.59%. The low variation between the various training conditions demonstrated that the implemented model is robust in terms of the error variation during the K-fold CV. Moreover, the daily *nRMSE* of each individual testing fold did not exceed a 5% performance threshold, which demonstrates that the model is sufficiently accurate for all training conditions.

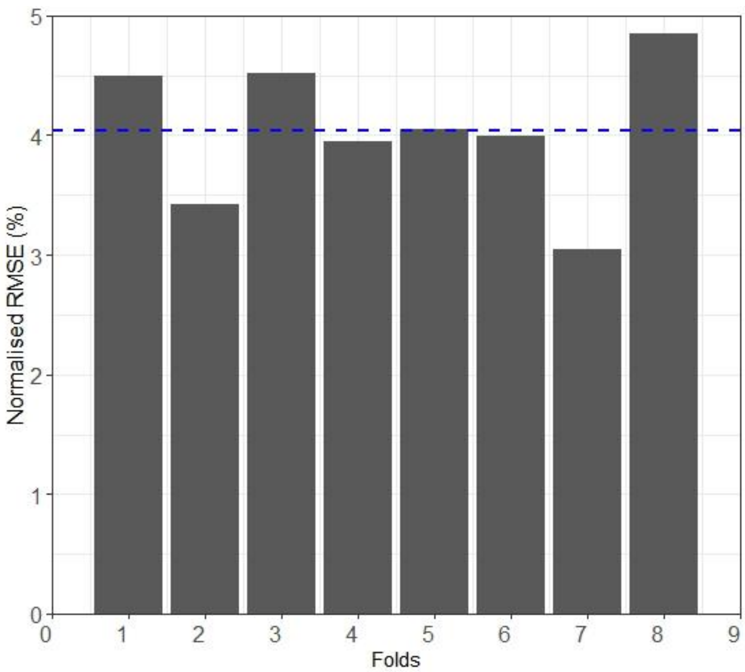


Figure 6 K-fold cross-validation nRMSE for the optimal ANN forecasting reference model (Mod4). The blue dashed line indicates the nRMSE obtained for all folds.

2.1.3 Lessons learnt

Utility grids with large share deployment of distributed PV systems are already facing a reflective conversion to modern digitally-enhanced technologies, which will allow the observability and regulation of distributed energy resources (DERs). This is the main reason why grid operators aim towards including intermittent renewable generation in their network planning models and optimization processes. To this end, the present electrification and decentralization tendencies are accelerating the conversion of the current power sector standard to completely expose system flexibility for high renewable penetration with innovative digital tool, with a specific direction to PV power generation forecasting [5].

To moderate power quality effects postured through large shares of PV systems, utilities necessitate PV power production forecasts for core generation dispatch and scheduling operations. Forecasting is a key enabler, which can safeguard operational and monetary integration of PV through structured associations with multiple power system flexibility innovations. Forecasts concentrate on the output power or the rate of change (ramp rate) of power of a single PV system or the aggregation of multiple PV systems. In particular, accurate PV power forecasting is a significant energy management component for utilities, which can conserve excessive spinning reserve, improve stability by optimally balancing consumption and generation, decrease integration and ancillary services costs and ensure unified integration of renewable energy sources (RES). Additionally, it enables the effective participation of PV plants and aggregated systems into electricity markets and allows distribution areas to turn into commercially viable microgrids that spur the value of low-cost solar electricity. An overview of the benefits provided by PV power forecasts for mitigating grid integration issues can be found in [6], [7], while a study that includes the targets for regional and point PV forecasting can be found in [8].

2.1.4 Next steps

The PV generation forecasting methodology was completed in M26 of the project (current month), therefore, the methodology was tested and evaluated against historical PV data-frames of parks located in Cyprus and also with historical PV data-frames of parks that are located in different climates. Furthermore, another research task, which is related to WP6 work is the integration of the proposed PV generation forecasting algorithms into the AFAT and FlexSupplier’s Toolkit (FST). Thus, the ESPs/aggregators will be able to increase their profits by making informed market decisions and minimizing errors and deviation from the declared position.

2.2 Market Price Forecasting

2.2.1 Introduction

Market price forecasting is part of the forecasting tools that will help ESP / Aggregator actors to participate effectively in distribution-level flexibility markets (DLFMs) and wholesale markets. Specifically, the market price forecasting tool will be a reliable forecasting tool that will be used to forecast the Day-Ahead market prices using historical data from specific areas. Also, it will be based on the operation framework and the regulatory context, which govern the Day-Ahead market. In this market, bidding for day D occurs at 12:00 of the previous day D-1. The market clearing price of day D is then published 43 minutes later at 12:43. This timeframe of day ahead market is depicted by the diagram of Figure 7.

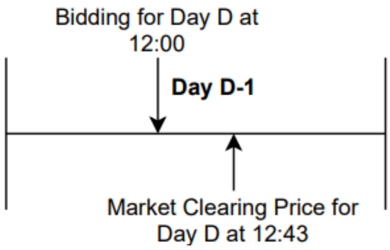


Figure 7: Day Ahead Market context

As it is stated in deliverable D4.2 [2], the motivation for creating such a tool is that it is anticipated to facilitate the risk assessment and thereby will provide insights to ESPs / Aggregators planning and management of their flexibility assets in view of increasing their profits. It will also enable RES owners to participate in the markets by offering high quality services. In general, there is an incentive to further improve the forecast and Market Forecast Accuracy Levels (MFAL).

The development of the market price forecasting tool is based on the UCY expertise in forecasting that is applied for first time in energy markets through the FLEXGRID project.

2.2.2 Extensive simulation results

The factors and physical variables that affect the electricity market prices are inter-related and uncertain. This renders the electricity price forecasting more challenging than other forecasting tasks, such as those for power production or demand forecasting. The core of the proposed forecasting algorithm is the Extreme Learning Machine (ELM). This algorithm as opposed to other neural network algorithms has short learning time with good generalization performance [9]. This quick learning feature is exploited by coupling the ELM with other methods such as bootstrapping in order to improve the forecasts.

ELM is a Single Layer Feedforward Neural network (SLFN) as shown in Figure 8. The weights w that connect the input with the internal layer are selected randomly. The biases of the hidden layer neurons are also determined randomly. The network is trained by computing the output weights (β) that match the training data x with the training target values y. This matching is expressed by equation 1 where L is the number of the hidden neurons and θ is neuron activation function,

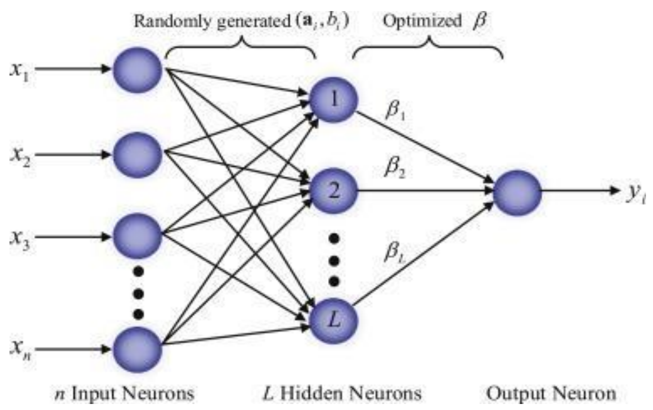


Figure 8: A typical structure of ELM

$$\sum_{i=1}^{L} \theta_i(x_i)\beta_i = \sum_{i=1}^{L} \theta\left(w_i \cdot x_j + b_i\right) = y_j \tag{1}$$

Casting equation (1) in the form,

$$H\beta = \Upsilon \tag{2}$$

where *H* is the Hidden Layer Output matrix given by

$$\mathrm{H} = \begin{pmatrix} \theta(w_1, b_1, x_1) & \cdots & \theta(w_L, b_L, x_1) \\ \vdots & \ddots & \vdots \\ \theta(w_1, b_1, x_n) & \cdots & \theta(w_L, b_L, x_n) \end{pmatrix}_{n\times L} \tag{3}$$

and β are the output weights and Y are the market prices. The training is achieved by computing the output weights β by solving equation 2 as follows,

$$\beta = H'\Upsilon \tag{4}$$

where H’ is the Moore-Penrose generalized inverse of the Hidden Layer (H) matrix.

The training data of the ELM consist of historical data of 23 consecutive days. These data are divided into 20 samples of 72 values and a different ELM is trained for each sample. That is to compute the vector β, using randomly selected weights (*w*) and biases, b, as described by equation 4.

This algorithm is used to forecast Day Ahead market prices for the Finnish and German Day Ahead markets. Historical market prices in Finland are obtained from the Nord Pool [10] while historical production forecast, consumption forecast and RES production forecast data are obtained from the Finnish TSO [11]. The historical data of Germany were provided by BnNetze. The historical data used were for the years 2019 and 2020.

As the market prices are highly volatile the market price samples were divided into three categories: those containing negative market prices, extremely high (positive) market prices and normal market prices. Negative prices usually occur in cases where renewable production is high and demand is relatively low, and on the contrary, extremely high (positive) prices occur in cases where the production from renewable is low and the activation of expensive power plants is required to cover a relatively high demand. In addition, the main characteristic of negative or extremely high (positive) prices is that they do not appear often and for this reason they are difficult to forecast. The performance of the proposed algorithm is evaluated against these three categories. The days were separated as follows: Days that showed at least one negative market price, days that showed at least one extremely high (positive) market price and days that had no negative or extremely high (positive) market price.

Negative market prices are market prices that are less than zero. Extremely high (positive) market prices are determined through a threshold that is defined by [12] ,

$$Threshold = \mu + 2\sigma \tag{5}$$

where μ is the sample mean and σ the sample standard deviation.

The threshold for each market was computed using the historical price data of the year 2019. The computed threshold for the Finnish is 74,61 $\left(\frac{€}{MWh}\right)$ while for the German market 68,70 $\left(\frac{€}{MWh}\right)$. Market prices exceeding these thresholds are considered extremely high while normal market prices are considered those that do not exceed the threshold.

Initially the algorithm was used to make 366 forecasts for the entire year 2020 and subsequently for each market price category. Also, the effect of activation functions was studied and for this reason different activation functions were used as activation functions dictate learning by determining the neurons that fire in the presence of characteristic features.

Figure 9 shows the average Mean Absolute Error (MAE) for each activation function for the various data sets. As can be seen, the sigmoid function gives better results compared to the other two functions.

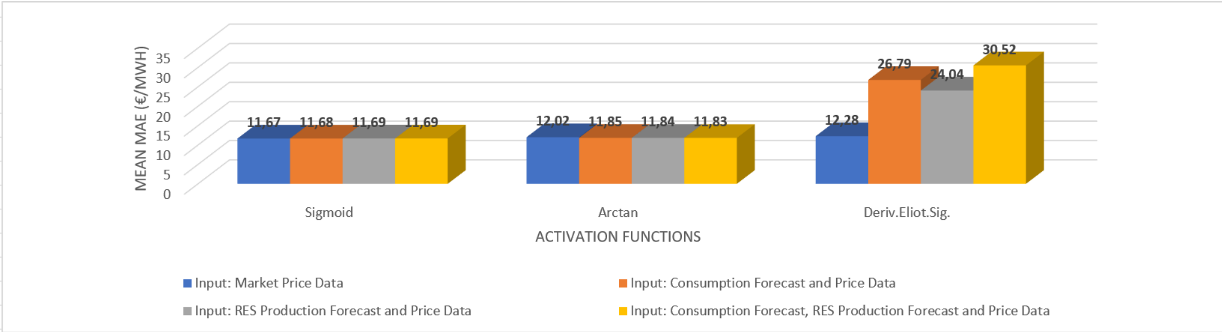


Figure 9: Average MAE for all days of 2020 using various historical data sets (Finland market)

The average MAE is relatively high because there are several market prices that exceeded the threshold (equation 5) and were considered extremely high (positive). Specifically, there were 186 market prices (more than is 74,61 $\left(\frac{€}{MWh}\right)$) which are extremely high. The histogram in Figure 10 shows the market price distribution of Finland for the year 2020.

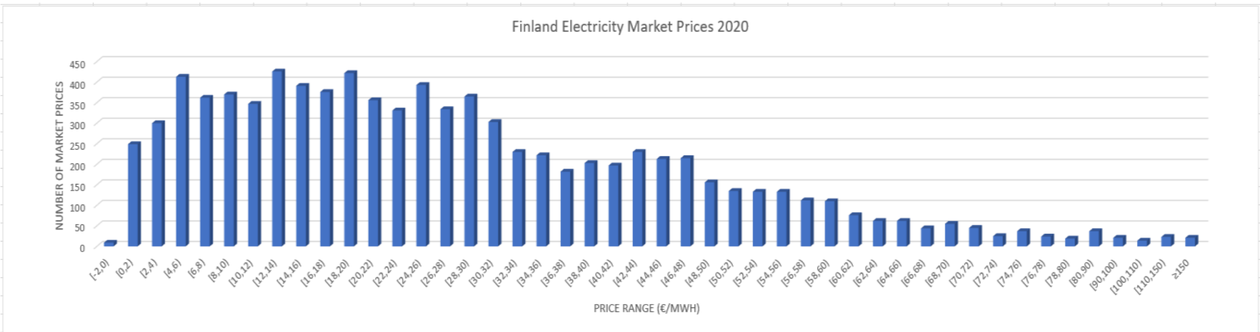


Figure 10: Market Price distribution of Finland for the year 2020

The Finnish market in the year 2020 showed several high market prices. There were 21 market prices which were over 150 $\left(\frac{€}{MWh}\right)$. On the contrary, the negative market prices that appeared were only 9 and were between [-2-0) $\left(\frac{€}{MWh}\right)$. Most prices were between [2-32) $\left(\frac{€}{MWh}\right)$.

Figure 11 shows the average of the actual market prices for each hour for all days of the year 2020 and the average of the forecast values per hour given by the algorithm. It can be seen that the forecast of extremely positive high values is not very accurate. However, from this figure it can be concluded that on average high price values are expected to occur at 7 a.m and 6 p.m.

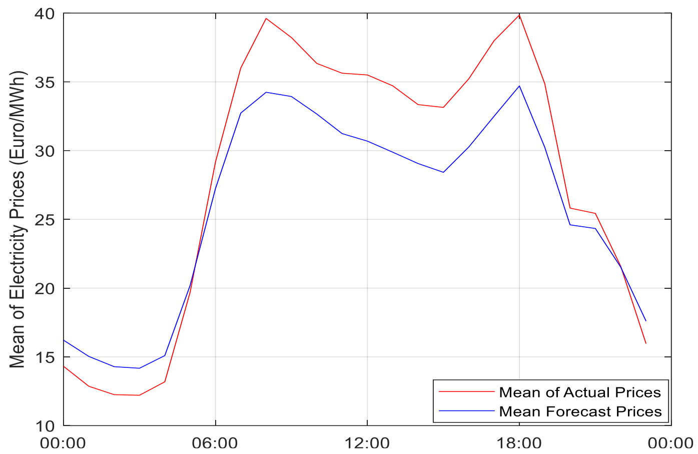
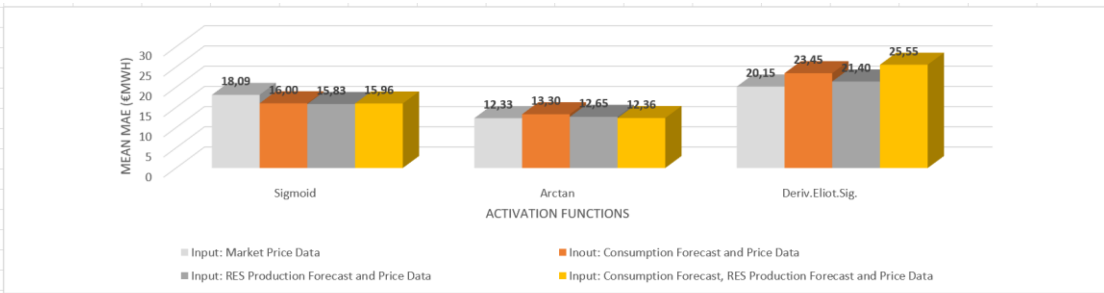
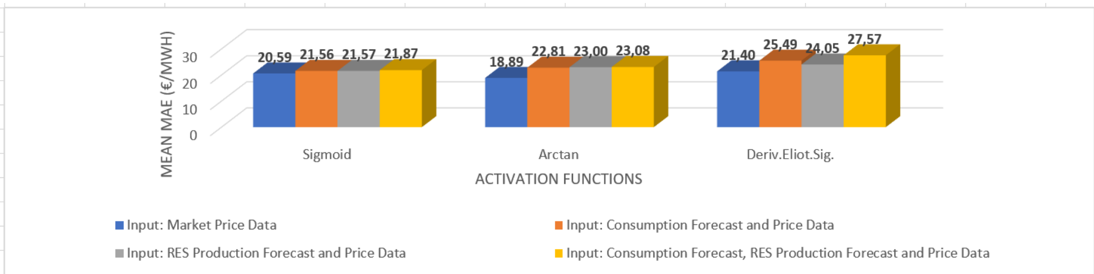


Figure 11: Comparison (on average) of actual market prices with the forecast market prices for all days of 2020 (Finland market), Mean MAE=11,67 $\left(\frac{€}{MWh}\right)$

a)



b)



c)

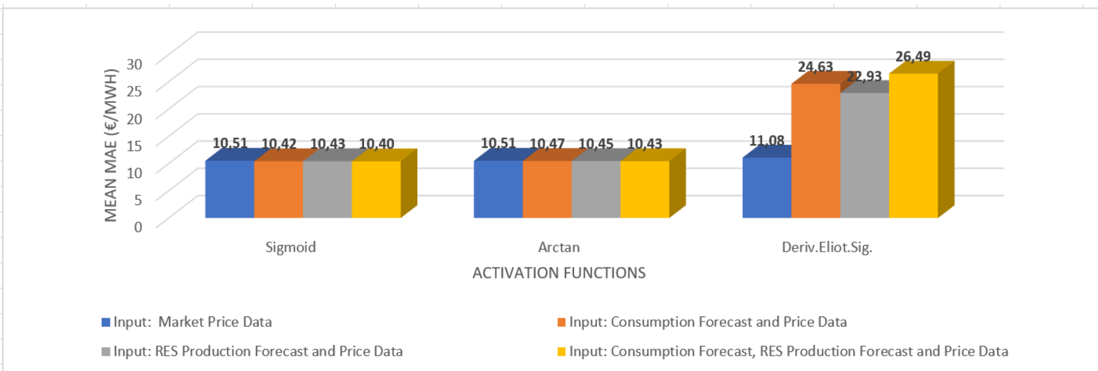
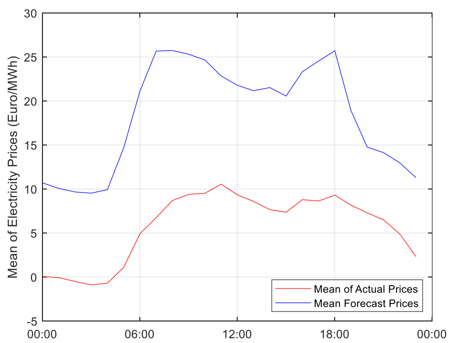


Figure 12: (Average) MAE calculation using different historical data sets (Finland Market) for each market price category: a) Negative market prices, b) Extremely high market prices and c) Normal market prices

Figure **12** shows the three different activation functions and datasets were used for each of the three categories of market prices. In the case of negative market prices, the arctan function gives the better result compared to the rest. Also, using only market prices gives slightly better results compared to other datasets. In the case of extremely high (positive) market prices the three activation functions gave similar results. However, the better result is obtained when using the arctan function together with market price data. In the case of normal market prices, the results are better than the results of the other two categories. The results given by the sigmoid and arctan are close. On the contrary, the derivative of Eliot Sigmoid gives the worst results. The better result is obtained in the case of the sigmoid and by incorporating the consumption forecast data, RES production forecast data and market price data which are entered together in the input of the algorithm.

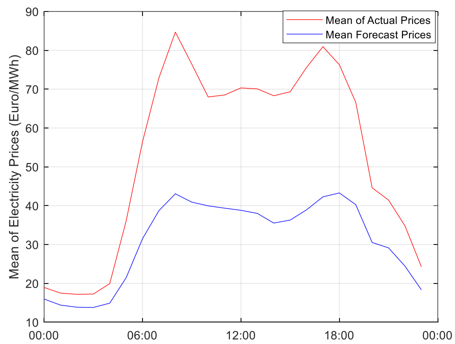
In Figure 13, the graphs show the average actual market prices per hour and the average hourly forecast market prices for each market price category. In case a) the negative market prices appear between 12-4 a.m and the algorithm cannot forecast them. In case b) where is the category of extremely high (positive) market prices it seems that the algorithm cannot forecast these prices while in case c) with normal market prices the algorithm gives better results. As mentioned above the algorithms cannot predict negative and extremely high (positive) market prices because they do not occur often.

a)



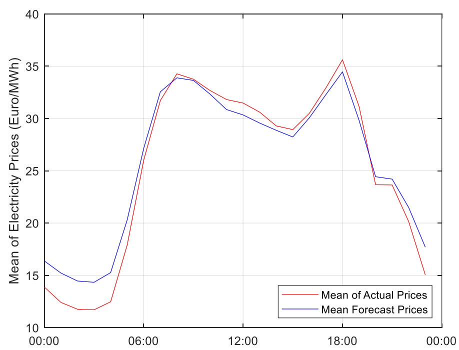
Average-MAE: 13,30

b)



Average-MAE: 18,89

c)



Average-MAE: 10,40

Figure 13: Comparison (on average) of actual market prices with the forecast market prices (Finland market) for each market price category: a) Negative market prices, b) Extremely high market prices and c) Normal market prices

Figure 14 shows the results (average MAE) of the algorithm using data from the German market. Activation functions give similar results. The better result is given by the sigmoid function using only market price data. If these results are compared with those given by the algorithm using the data from Finland, it is better. The reason is that Germany showed several negative market prices (some were very negative) compared to Finland but did not have such extremely high (positive) market prices. Most market prices were between (25-35] $\left(\frac{€}{MWh}\right)$. The market price distribution of Germany is shown in Figure 15.

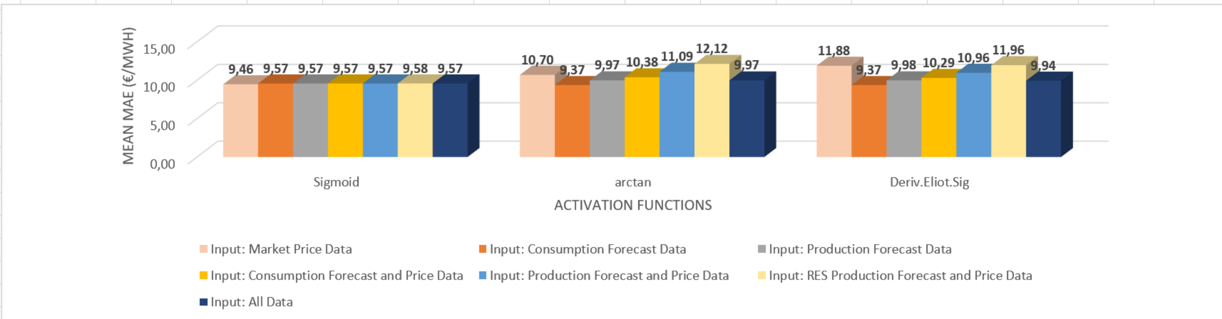


Figure 14: Average MAE for all days of 2020 using various historical data (German market)

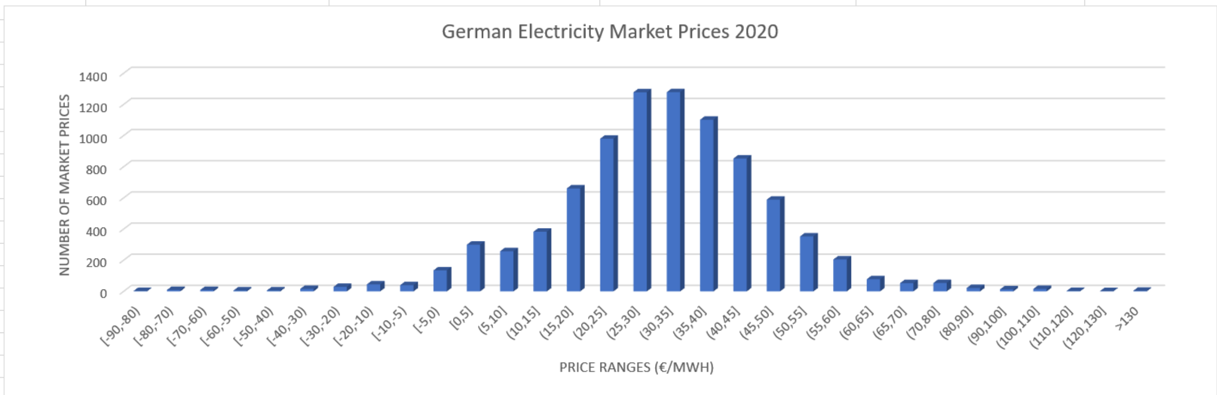


Figure 15: Market Price distribution of German for the year 2020

Figure 16 shows the average of the actual market prices per hour and the average of the forecast market prices per hour given by the algorithm for all days of the year 2020. As it can be seen the forecast of the extremely high (positive) market prices is not very precise.

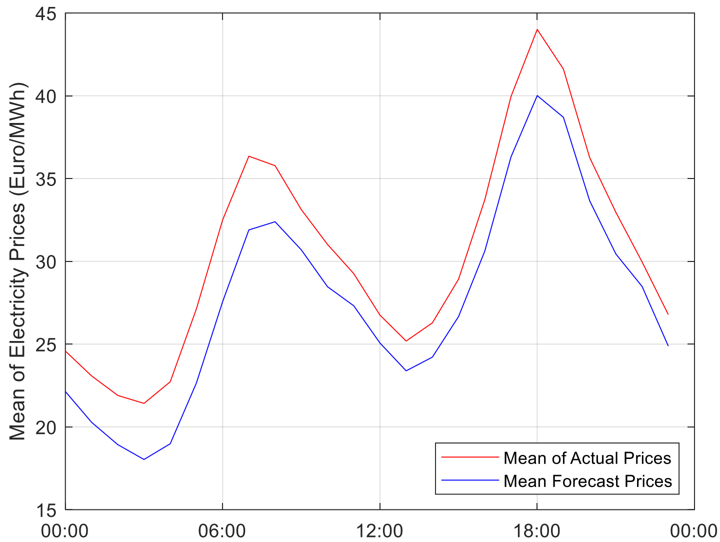


Figure 16: Comparison (on average) of actual market prices with the forecast market prices for all days of 2020 (German market), Mean MAE=9,37 $\left(\frac{€}{MWh}\right)$

Figure 17 shows the average MAE resulting from the comparison of the actual market prices and forecast market prices given by the algorithm for each market price category. In the case of negative market prices, the results given by the activation functions do not differ much. Also, the average MAE is relatively high because there are several negative market prices. The better results are given by the arctan and derivative Eliot sigmoid functions using consumption forecast data as the input.

In the case of extremely high (positive) market prices the sigmoid function gives a better result compared to the other two functions. The better result is obtained using market price data. In the case of normal market prices, the results are better compared to the other two categories. Using the sigmoid function with market price data gives the better result.

Figure 17: (Average) MAE calculation using different historical data sets (German Market) for each market price category: a) Negative market prices, b) Extremely high market prices and c) Normal market prices

In Figure 18, the graphs show the average actual market prices per hour and the average hourly forecast market prices for each market price category. As the graphs show, the algorithm cannot forecast negative or extremely high (positive) market prices because they do not appear as often. On the contrary, in the case of normal market prices the algorithm gives much better results.

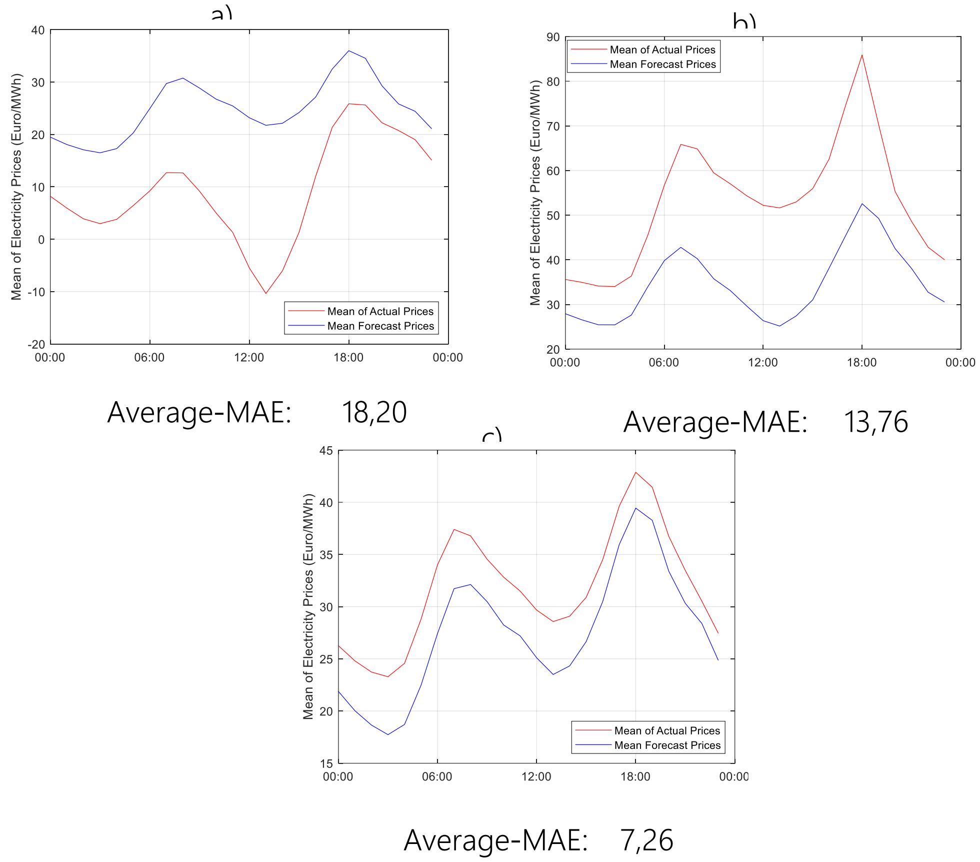


Figure 18: Comparison (on average) of actual market prices with the forecast market prices (German market) for each market price category: a) Negative market prices, b) Extremely high market prices and c) Normal market prices

2.2.3 Lessons learnt

The histogram shown in Figure 19 shows the mean of the difference between production forecast and consumption forecast (Production Forecast – Consumption Forecast) for each market price ranges in Germany for the year 2020. From this histogram an important conclusion that can be drawn is the nature of the market. That is, the balance between consumption and production, and consequently the market.

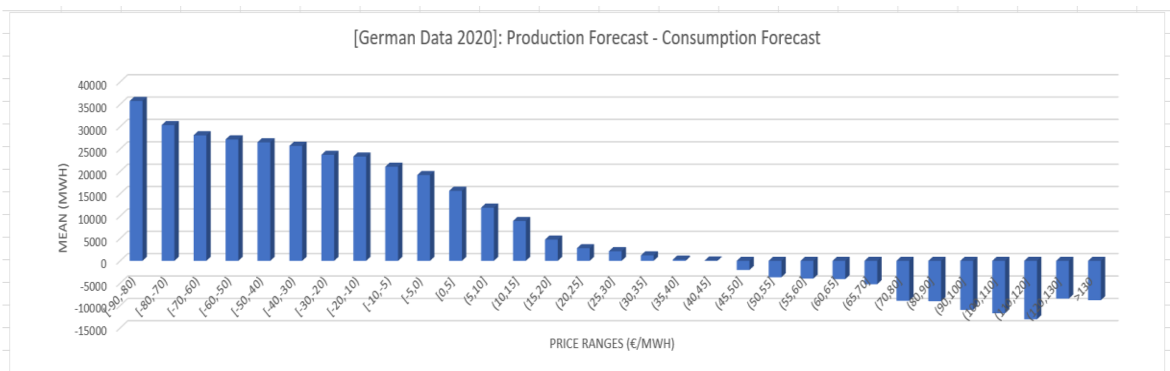


Figure 19: Production Forecast – Consumption Forecast (Balance between production forecast and consumption forecast is close to zero: 35-40 $\left(\frac{€}{MWh}\right)$)

Market price forecasting is very important for market participants because they will be given the opportunity to address risks and have information that will help in better planning that will bring them more profits. However, market price forecasting has many challenges due to the dependence of market prices on many external factors, such as fuel prices, weather conditions, production, demand, etc. In addition, the need to create an electricity grid based on renewable technologies has resulted in market price volatility becoming even greater. That is why in many cases the market price is negative or extremely high (positive). The negative price is due to the fact that the high production of renewables which has low marginal costs meets production from inflexible power plants (e.g. nuclear power plants, lignite power plants and CHP plants) and demand is low. Extremely high (positive) market prices exist when demand is very high, production from renewables is low and the integration of high-cost power plants is necessary to meet high demand. But extreme market prices are very difficult to forecast because they do not appear often. Therefore, creating a flexible forecasting tool that can forecast outliers (negative market prices or extremely high (positive) market prices) will be a very important tool especially for new market participants (e.g. aggregator) who will be able to compete with others by providing high quality services.

2.2.4 Next steps

The next steps are to improve the predictability of the algorithm, in cases where there are negative values or extremely high values. One thought is to correct the forecast market prices given by the algorithm based on some ratios. That is, a ratio that can help correct forecasts is Production Forecast / Forecasted Residual Load or Consumption Forecast/ Forecasted Residual Load (Forecasted Residual Load= Consumption Forecast – RES Production Forecast). Figure 20 shows a histogram in which there is the mean of the ratios for each market price ranges.

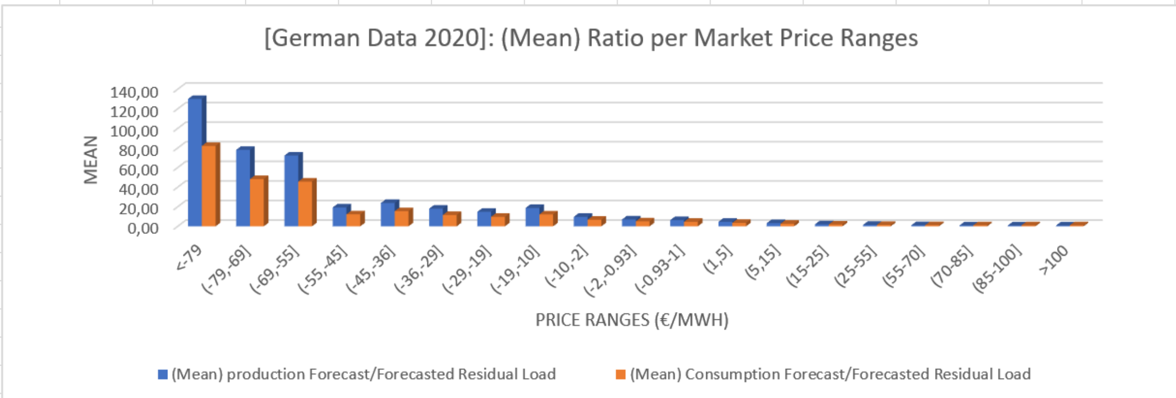


Figure 20: Mean of ratios for each market price ranges

When the market prices are negative the Production Forecast / Forecasted Residual Load is very high because the production forecast is much higher than the consumption forecast and the forecasted residual load is small because the renewable production forecast is low (for market prices less than -55 $\left(\frac{€}{MWh}\right)$ the mean Ratio is above 70). As the market price increases the ratio decreases because the production forecast decreases, the consumption forecast increases and the renewable production forecast decreases (for over 70 $\left(\frac{€}{MWh}\right)$ the mean ratio is less than 1).

A similar situation applies in the case of Consumption Forecast / Forecasted Residual Load. For negative market prices the ratio is high because the forecasted residual load is low because the renewable production forecast is high. While as the market price increases the ratio decreases because the forecasted residual load increases due to the reduction of renewable production forecast. So, a high ratio will mean that most likely the market price will be negative and when it is low it will mean that the market price is extremely positive high.

After M26, the market price algorithm will be integrated into the platform. This algorithm belongs to the forecasting engine, which will reside in the Automated Flexibility Aggregation Toolkit (AFAT) and FlexSupplier's Toolkit (FST). The main feature of the platform is the modular-by-design S/W architecture, where the APIs give the inputs to the algorithm and then will transfer the results to FLEXGRID ATP to be exploited by ESPs/Aggregators users.

3 ESP’s OPEX minimization problem (UCS 2.1)

3.1 Introduction

This chapter deals with the research problem of UCS 2.1. In the center of the problem, we observe scheduling actions from an Energy Service Provider’s (ESP) perspective. In the scope of the FLEXGRID project, ESP is considered as a profit-oriented market participant which, in the most general case, may make contractual arrangements with various types of flexibility assets (e.g. DSM, RES, storage). Furthermore, it may participate in energy and capacity wholesale markets, sell the energy on the retail market and take part in the near-real-time flexibility markets. For the purposes of UCS 2.1., the model is not network aware, so the exact location of Battery Storage Units (BSUs) is not relevant, nor are other grid constraints. The optimal scheduling algorithm is the base for the operational expenditure minimization problem, in that manner, following markets are considered:

- Day-ahead Energy Market (DA-EM) operated by the MO
- Day-ahead Distribution-Level Flexibility Market (DA-DLFM) operated by a novel market entity introduced by FLEXGRID market architecture, called FMO
- Intraday Energy Market (IDM) operated by the MO
- Near-real-time Balancing Market (BM) operated by the TSO

Within FLEXGRID project’s context and this UCS, we **propose two novel energy market architectures. Namely, 1) Reactive and 2) Proactive Distribution Level Flexibility Market (R- and P-DLFM).** While the R-DLFM is fully compatible with today’s EU regulatory framework, P-DLFM would require same adjustments. Participation in the different markets provides the ESP with the opportunity to reduce its operational expenditures (OPEX) using a scheduling algorithm. Accounting for the price uncertainty in each of the modeled markets, the optimal scheduling algorithm produces such strategy which results in higher profits for the ESP user.

In this market environment, **a BSU owner can decrease its OPEX by providing energy and ancillary services in various markets,** including the proposed x-DLFM market. In UCS 2.1, **we consider an ESP as a market stakeholder, which owns BSUs and may participate in markets at the transmission and distribution level.**

3.2 Problem statement and summary of FLEXGRID research contributions

Excluding the distribution and transmission system operators as textbook examples of natural monopolies, modern electrical power systems lean towards free market principles. Hence, they are open for participation to any interested party that meets certain technical and economical requirements. ESPs’ portfolios may be composed of a wide variety of services and technologies (demand response, renewable energy resources – RES, battery storage, etc.) and they may bid in different electricity. It is the diversity of technologies in their portfolio and their availability to participate in various markets that drives the profit amplitudes between the optimal and sub-optimal solutions. More specifically, each technology has its own technical peculiarities, whereas the markets have specific rules.

Hence, such complementarity may result in high profits, but also in high costs in case of flawed modelling and poor predictions. Competitive markets do not tolerate sub-optimal strategies, so it is in the players' best interest to ensure optimal market performance to prevail their rivals. Furthermore, the complexity of the problem at hand increases with the addition of new markets. Considering the intermittent nature of RES, an important question is how to accommodate high shares of RES in the total energy mix while ensuring safe and reliable power supply at all times. FLEXGRID proposes a novel distribution-level flexibility market (DLFM) as a solution to facilitate high-RES penetration and an active role of consumers. Existence of the DLFM creates, on the one hand, opportunities for the Transmission System Operator (TSO) and the Distribution System Operator (DSO) to procure flexibility services and avoid network problems. On the other hand, the DLFM presents an opportunity for profit-oriented entities, e.g., ESPs, to generate profit by offering their services in a new market. As ESPs already take part in the existing markets, it is important for them to generate a schedule that yields higher overall profit. Hence, based on the different DLFM setups, flexibility providers will have to pay even more attention to their scheduling to minimize deviations from their market position, which may result in the balancing market penalties, and reduce their inability to provide a contracted service. Such failure may result in disqualification from certain markets. We find it interesting and important to examine the consequences of different market setups and simplicity of integration into the current market design. The more efficient the newly proposed x-DLFM is, the faster and higher RES integration may be achieved. Therefore, this UCS examines the behaviour of a profit-oriented market player that bids not only in the conventional markets, but also in the newly proposed DLFM. Moreover, an analysis of the ESP's behaviour under different market setups (sequence of the market clearing), may identify the most promising approach where both, the entity that procures the flexibility (i.e. DSO), and the entity that offers flexibility services will indeed benefit from such market setup. Specifics of different x-DLFM setups are examined focusing on how they fit the existing market structure. In that manner, the DAM, the IDM, the BM and two versions of the DLFM are modelled. The developed optimization strategy finds a schedule that brings the highest utility to the flexibility provider, considering the uncertainties, constraints and characteristics of each individual market and the market structure in general. This research has also been published in IEEE Access journal [13].

Considering ongoing trends in the development of distribution-level flexibility markets and overall shift towards RES, this work proposes an optimal scheduling algorithm to help ESPs minimize OPEX when participating in different markets. The ESP calculates its optimal strategy according to the known or predicted prices in all markets, regardless of the possibility that in some markets (e.g. x-DLFM) the ESP may be a price-taker entity. The FLEXGRID UCS 2.1 research contributions may be summarized as follows:

- Introduction of market design that incorporates two versions of a local flexibility market. One version is fully compatible with the existing structures, while the latter would require adjustments.
- Scheduling algorithm that considers market uncertainty. The IDM uncertainty, due to its continuous trading nature, is addressed using robust optimization, while stochastic optimization is used for DAM, BM and DLFM, which are auction-based markets.

- The effect of different definition of the DLFM is examined (R- and P-) and results are analysed

3.3 System Model

For the research purposes of UCS 2.1, we consider a market architecture that consists of DAM, IDM, BM and proposed Distribution-Level Flexibility Market. Two versions of the DLFM are modelled. R-DLFM follows the clearing process of the DAM without the “power” to change the DAM schedule. Hence, if the DLFM alters the day-ahead energy market dispatch of the ESP’s FlexAssets participating in the DAM, ESP will have to balance their portfolio in the BM. The P-DLFM precedes the DAM clearing. Those two market schemes present the circle of modelled markets where ESP, in the context of this UCS, is able to participate in (see figure below for the better understanding). The range colour depicts transmission level markets, while yellow and blue represent two versions of the DLFM. It is also important to notice that the model is not network-aware, so network constraints are not taken into consideration in any of the mentioned markets.

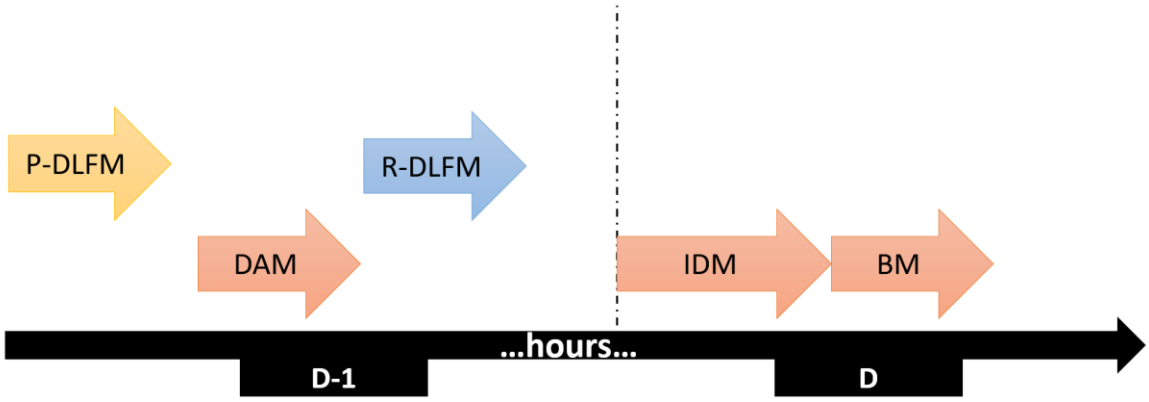


Figure 21 – Different DLFM setups

The main difference between the P-DLFM and the R-DLFM is their clearing time. The P-DLFM clears before the DAM, while the RDLFM clears between the DAM and the IDM. Both DLFMs are distribution-level markets and operated by the flexibility market operator. Only one of the two proposed DLFMs can operate as they would collide if both existed at the same geographical location. To analyse their characteristics and repercussions on the battery storage unit operations, the scheduling algorithm versions are based on the chronological location of the DLFM.

3.4 Problem formulation

3.4.1 R-DLFM architecture

In the R-DLFM market setup, the proposed flexibility market follows the DAM. The sequence continues with the IDM and, finally, the BM as a penalization instrument for the deviations from the market schedule. Accordingly, the level of available information differs from one market to another. The DAM schedule needs to be decided without knowing the prices in any of the markets, while the bidding strategy in the R-DLFM is determined with the DAM cleared price and quantity information. Battery storage operation in the IDM is planned knowing both the DAM and the R-DLFM prices, whereas trading in the BM is merely a consequence of the actions in the previous markets. The battery storage unit operator's optimal bidding in the DAM, R-DLFM, IDM and BM markets is formulated as follows:

$$\underset{\omega}{\mathrm{Max}} \sum_{t=0}^{T} ((dis_t^{DA} - ch_t^{DA}) \cdot \sum_{s}^{S} (\pi_s \cdot \lambda_{s,t}^{DA}) \quad +$$

$$\sum_{s}^{S} [(f_{s,t}^{\uparrow} \cdot \sum_{k}^{K} \pi_{s,k} \cdot \lambda_{s,k,t}^{flex\uparrow}) - (f_{s,t}^{\downarrow} \cdot \sum_{k}^{K} \pi_{s,k} \cdot \lambda_{s,k,t}^{flex\downarrow})] \ +$$

$$\sum_{s}^{S} \sum_{k}^{K} (\pi_{s,k} \cdot \lambda_{s,k,t}^{ID_{avg}} \cdot (dis_{s,k,t}^{ID} - ch_{s,k,t}^{ID})) + \sum_{s}^{S} \pi_{s,k} \cdot (-dev_{s,k,t}^{\uparrow} \cdot \lambda_{s,k,t}^{BM,\uparrow} - dev_{s,k,t}^{\downarrow} \cdot \lambda_{s,k,t}^{BM,\downarrow})$$

$$- \underset{b_{s,k,t}}{\mathrm{Max}} \sum_{s} \sum_{t} \pi_{s,k,t} (ch_{s,k,t}^{ID} - dch_{s,k,t}^{ID}) \cdot \delta\lambda_{s,k,t}^{ID} \cdot b_{s,k,t}$$

$$s.t. \sum_{t} b_{s,k,t} \leq \Gamma \,, 0 \leq b_{s,k,t} \leq 1, \qquad \forall \mathrm{s,k,t} \qquad (1)$$

Subject to:

$$f_{s,t}^{\uparrow} \leq \bar{F}_{s,t}^{\uparrow}, \qquad \forall \mathrm{s,t} \quad (2)$$

$$f_{s,t}^{\downarrow} \leq \bar{F}_{s,t}^{\downarrow}, \qquad \forall \mathrm{s,t} \quad (3)$$

$$dis_t^{DA} - dev_{s,k,t}^{\downarrow} \leq \bar{P}^{dch} \cdot x_t, \qquad \forall \mathrm{t} \quad (4)$$

$$ch_t^{DA} - dev_{s,k,t}^{\uparrow} \leq \bar{P}^{ch} \cdot (1 - x_t), \qquad \forall \mathrm{t} \quad (5)$$

$$dis_{s,k,t}^{ID} \leq \bar{P}^{dch} \cdot x_t^{ID}, \qquad \forall \mathrm{s,k,t} \quad (6)$$

$$ch_{s,k,t}^{ID} \leq \bar{P}^{ch} \cdot (1 - x_t^{ID}), \qquad \forall \mathrm{s,k,t} \quad (7)$$

$$f_{s,t}^{\uparrow} \leq P^{max,dch} + ch_t^{DA} - dev_{s,k,t}^{\downarrow} + ch_{s,k,t}^{ID} - dis_t^{DA} + dev_{s,k,t}^{\uparrow} - dis_{s,k,t}^{ID}, \qquad \forall \mathrm{s,k,t} \quad (8)$$

$$f_{s,t}^{\downarrow} \leq P^{max,ch} + dis_t^{DA} - dev_{s,k,t}^{\uparrow} + dis_{s,k,t}^{ID} - ch_t^{DA} + dev_{s,k,t}^{\downarrow} - ch_{s,k,t}^{ID}, \qquad \forall \mathrm{s,k,t} \quad (9)$$

$$g_{s,k,t} = ch_t^{DA} - dev_{s,k,t}^{\downarrow} + ch_{s,k,t}^{ID} + f_{s,t}^{\downarrow} - dis_t^{DA} + dev_{s,k,t}^{\uparrow} - dis_t^{ID} - f_{s,t}^{\uparrow}, \qquad \forall \mathrm{s,k,t} \quad (10)$$

$$g_{s,k,t} = c_{s,k,t} - d_{s,k,t}, \qquad \forall \mathrm{s,k,t} \quad (11)$$

$$c_{s,k,t} \leq \bar{P}^{ch} \cdot x_{s,k,t}, \qquad \forall \mathrm{s,k,t} \quad (12)$$

$$d_{s,k,t} \leq \bar{P}^{dch} \cdot \left(1 - x_{s,k,t}\right), \qquad \forall \mathrm{s,k,t} \quad (13)$$

$$soe_{s,k,t} = soe_{s,k,t-1} + c_{s,k,t} \cdot \eta^E - d_{s,k,t}, \qquad \forall \mathrm{s,k,t} \quad (14)$$

$$0 \leq soe_{s,k,t} \leq C^E, \qquad \forall \mathrm{s,k,t} \quad (15)$$

$$soe_{s,k,24} > SOE_{s,k,0}, \ \forall \mathrm{s,k}, \qquad (16)$$

$$soe_{s,k,t} = \sum_{i=1}^{I-1} soe_{t,i,s,k}, \ \forall \mathrm{s,k,t} \quad (17)$$

$$soe_{t,i,s,k} \leq R_{i+1} - R_i, \qquad \forall \mathrm{s,k,i,t} \quad (18)$$

$$\Delta soe_{s,k,t} = F_1 + \sum_{i=1}^{I-1} \frac{F_{1+1} - F_i}{R_{i+1} - R_i} \cdot soe_{t-1,i,s,k}, \ \forall \mathrm{s,k,i,t} \quad (19)$$

$$c_{s,k,t} \leq \frac{\Delta soe_{s,k,t}}{\Delta t^h \cdot \eta^E}, \qquad \forall \mathrm{s,k,t} \quad (20)$$

The objective function (1) follows the chronological order of the markets and information availability, taking into account the price uncertainties. The set of variables is:

$$\omega = dis_t^{DA}, ch_t^{DA}, f_{s,t}^{\uparrow}, f_{s,t}^{\downarrow}, dis_t^{ID}, ch_t^{ID}, dev_{s,k,t}^{\uparrow}, dev_{s,k,t}^{\downarrow}, b_{s,k,t}, x_t^{DA},$$
$$x_{s,k,t}^{ID}, x_{s,k,t}, g_{s,k,t,} c_{s,k,t}, d_{s,k,t}, soe_{s,k,t}, soe_{t,i,s,k}, \Delta soe_{ts,j,t}$$

The first term in (1) represents the DAM charging (ch_t^{DA}) and discharging (dis_t^{DA}) schedule that needs to be decided before knowing the DAM prices. Probabilities π_s weigh the DAM price scenarios $\lambda_{s,t}^{DA}$ to obtain the expected DAM price. The second row reflects the flexibility market, whose prices depend on the realized DAM price clearing scenario s, deciding the up and down flexibility ($f_{s,t}^{\uparrow}, f_{s,t}^{\downarrow}$). The third row models the IDM, which clears after the DAM and the R-DLFM. Due to the nature of the IDM (it is not an auction based, but a continuous pay-as-bid market), instead of relying on stochastic optimization, we employ the robust optimization, which reflects the confidence in the IDM bidding actions. Since the IDM is pay-as-bid with continuous trading, there is no single market clearing IDM price. In other words, the traded price differs in time up to the cut-off time, usually 15 or 30 minutes before the delivery time. Because of this, we find scenarios that relate IDM prices throughout all hours inappropriate and utilize robust optimization, which models the skilfulness (and luck) of the battery storage operator. In the objective function (1) the fifth and the sixth rows represent the robust sub-problem which is then transformed to its dual form, converting the inner problem to a minimization problem. The inner minimization problem can then be omitted as the outer maximization of the objective function and inner negative minimization have the same optimization direction. In a nutshell, robust optimization[2] tries to inflict as much damage as possible, meaning that for an average IDM price from the third term $\lambda_{s,k,t}^{ID_{avg}}$, the robust optimization adds or subtracts value $\lambda_{s,k,t}^{ID_{avg}}$ in the direction that it worse for the overall objective function. This means that if a battery storage is buying energy at a specific time period in the IDM, the price would be higher than average, and if it is selling the energy, the price would be lower. Parameter Γ is the budget of uncertainty that determines how many of the total observed time units will be affected by the robust optimization. If, out of 24 observed time periods, Γ equals 7, only seven worst possible time periods will be affected. On the other hand, setting Γ to 0 creates an optimistic case where no robust optimization is considered, but only the average prices, which is equivalent to the deterministic approach. Binary variable $b_{s,k,t}$ must be lower or equal to the budget of uncertainty (Γ). Lastly, the fourth row in objective function (1) represents leveling the market positions in the BM. As the realization of actions in this market is considered as a consequence of the previous actions (i.e. deviations from the schedule), the BM is not considered as a separate stage, thus the model complexity is somewhat relaxed.

[2]] B. L. Gorissen, I. Yanikoglu, and D. den Hertog, "A practical guide to robust optimization," Omega, vol. 53, pp. 124—137, June 2015.

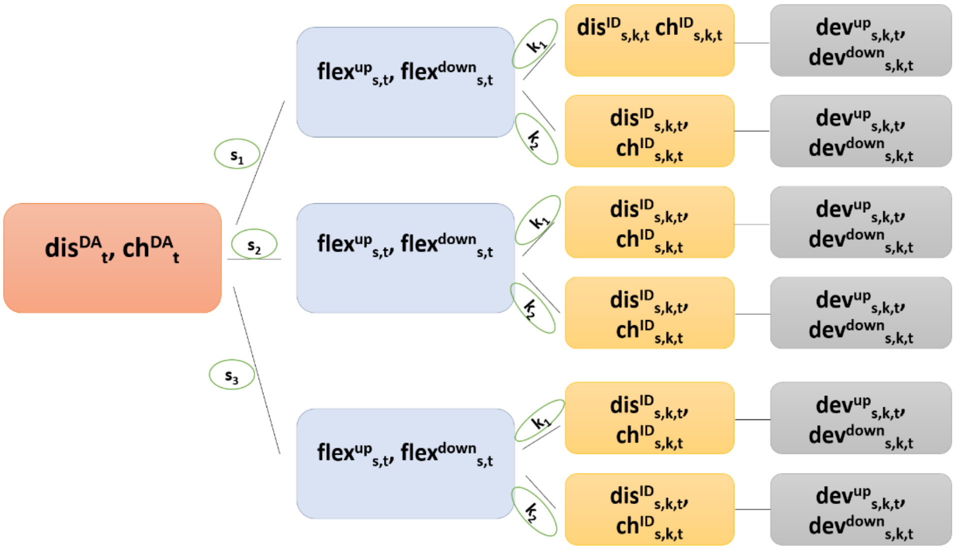


Figure 22 - R-DLFM concept decision stages

Figure 22 illustrates the above-described three-stage market setup considering the chronological order of the market clearing times and scenario branching. Please note that the IDM prices are generated as a robust uncertainty set, so for each scenario they may be in the range $< \lambda^{IDavg}_{s,k,t} - \delta\lambda^{ID}_{s,k,t}, \lambda^{IDavg}_{s,k,t} + \delta\lambda^{ID}_{s,k,t} >$ and the BM is a consequence rather than a separate stage. Description of the variables and parameters used in the model is available in the table belove. For better understanding, the parameter names in the model are in regular font, while the variable names are in italic. Constraint (2) denotes the maximum upward flexibility needed in each scenario and hour, while (3) does the same but for the downward flexibility. The DAM battery storage discharging, and charging are limited by the respective maximum discharging and charging powers in (4) and (5), considering binary variable x^{DA}_{t} that forbids simultaneous charging and discharging. In the same manner, charging and discharging process in the IDM is modelled by constraints (6) and (7). The available flexibility power capacity, depending on the activities in the DAM and IDM, is constrained in (8) for the upward direction, and in (9) for the downward direction. The purpose of the flexibility constraints is to restrict flexibility in each direction to the physically available capacities. It takes into consideration the maximum charging/discharging power and activities planned in other markets. For example, if down flexibility is needed and discharging activities in the DAM and IDM are planned, the battery storage may provide down reserve capacity that exceeds its power rating as a portion of the down reserve is provided by simply reducing the planned discharging quantity in the DAM and IDM, and, on top of that, the battery storage can start charging up to its full power capacity. Equation (10) calculates the battery's net charging/discharging activity considering all markets where it participates, including the deviations at the balancing stage. Constraint (11) connects the net battery activity with its physical charging and discharging processes. Variable $c_{s,k,t}$ in constraint (12) limits the battery's overall charging activity to its rated power, while constraint (13) does the same for the discharging variable $d_{s,k,t}$. Equation (14) models the battery's state of energy (*soe*) during the observed period depending on actions in all the markets. State of energy is constrained with the lower and the upper bound in (15). Constraint (16) ensures that state of energy at the end of the observed period is not below the state of energy at the beginning of the observed period. Constraints (17)– (20) model the battery charging capacity acknowledging the fact that the battery charging ability reduces as its state of energy increases due to entering the constant-voltage phase of the charging process. More information on this process and the model is available in [14]. Variable $\delta soe_{t,s}$denotes the maximum amount of energy that can be charged into the battery in a single time step depending on its state of energy. This dependence is obtained from measuring the battery charging characteristic in a laboratory. Since this characteristic is nonlinear, it is approximated by a piece-wise linear function that results with fitting parameters R_i and F_i. In that manner, state of energy is decomposed into $I-1$ segments, where I stands for the number of breakpoints of the piecewise function (constraint (17)). Constraint (18) limits the energy of each linear segment, while (19) determines the maximum energy charging ability of the respective battery at each time period. Finally, (20) is the maximum charging power constraint.

Table 1 - Parameters and variables for R- and P-DLFM setup

Description	Variable		Unit
	R-DLFM	P-DLFM	
Budget of uncertainty binary variable	$b_{s,k,t}$	$b_{k,s,t}$	-
Battery charging	$c_{s,k,t}$	$c_{k,s,t}$	MW
DAM charging	ch_t^{DA}	$ch_{k,t}^{DA}$	MW
IDM charging	$ch_{s,k,t}^{ID}$	$ch_{k,s,t}^{ID}$	MW
Battery discharging	$d_{s,k,t}$	$d_{k,s,t}$	MW
Maximum amount of energy that may be charged into battery	$\Delta soe_{s,k,t}$	$\Delta soe_{k,s,t}$	MWh
DAM schedule downward deviation	$dev_{s,k,t}^{\downarrow}$	$dev_{k,s,t}^{\downarrow}$	MWh
DAM schedule upward deviation	$dev_{s,k,t}^{\uparrow}$	$dev_{k,s,t}^{\uparrow}$	MWh
DAM discharging	dis_t^{DA}	$dis_{k,t}^{DA}$	MW
IDM discharging	$dis_{s,k,t}^{ID}$	$dis_{k,s,t}^{ID}$	MW
Downward flexibility	$f_{s,t}^{\downarrow}$	$f_s^{\downarrow}$	MW
Upward flexibility	$f_{s,t}^{\uparrow}$	$f_t^{\uparrow}$	MW
Net battery activity	$g_{s,k,t}$	$g_{k,s,t}$	MW
State of energy of the battery	$soe_{s,k,t}$	$soe_{k,s,t}$	MWh
Overall ch/dis activity binary variable	$x_{s,k,t}$	$x_{k,s,t}$	-
DA ch/dis activity binary variable	$x_{s,k,t}^{DA}$	$x_{k,s,t}^{DA}$	-
ID ch/dis activity binary variable	$x_{s,k,t}^{ID}$	$x_{k,s,t}^{ID}$	-
Description	Parameter		Unit
	R-DLFM	P-DLFM	
Downward BM prices	$\lambda_{s,k,t}^{BM,\downarrow}$	$\lambda_{k,s,t}^{BM,\downarrow}$	€/MWh
Upward BM prices	$\lambda_{s,k,t}^{BM,\uparrow}$	$\lambda_{k,s,t}^{BM,\uparrow}$	€/MWh
Battery capacity	C^E		MWh
Full cylce efficiency	η		-
Maximum amount of energy that can be charged at specific battery soe breakpoint i	F_i		MWh
Uncertainty budget	Γ		-
DA prices	$\lambda_{s,t}^{DA}$	$\lambda_{k,s,t}^{DA}$	€/MWh
FM downward prices	$\lambda_{s,k,t}^{flex,\downarrow}$	$\lambda_{k,s,t}^{flex,\downarrow}$	€/MWh
FM upward prices	$\lambda_{s,k,t}^{flex,\uparrow}$	$\lambda_{s,k,t}^{flex,\uparrow}$	€/MWh
IDM prices	$\lambda_{s,k,t}^{ID}$	$\lambda_{k,s,t}^{ID}$	€/MWh
Maximum charging power	$\overline{P}^{ch}$		MW
Maximum discharging power	$\overline{P}^{dch}$		MW
Capacity of each state of energy battery segment i as a portion of the installed battery capacity	R_i		MWh
Starting SOE	$SOE_{s,k,0}$	$SOE_{k,s,0}$	MWh
Scenario probability first branching	π_s	π_k	-
Scenario probability second branching	$\pi_{s,k}$	$\pi_{k,s}$	-

3.4.2 P-DLFM architecture

The objective function and the associated constraints in the P-DLFM model share the same methodology and form as the R-DLFM. The main difference is that, in contrast to the R-DLFM setup described in the previous subsection, in the P-DLFM market setup the flexibility market precedes the DAM. Although each market is modelled following the same principles as in the R-DLFM market setup, the chronological order changes. To present the P-DLFM in concise but understandable manner,

Table 1 lists all variables and parameters used in both market setups. For the sake of clarity, indices for all variables and parameters are listed in the table chronologically. For instance, although variables with sets of indices s, k, t and k, s, t are identical in mathematical sense, we explicitly follow the chronological order to emphasize the order of market clearings. Moreover, the objective function (21) is explicitly written to emphasize the differences:

$$\underset{\omega}{\text{Max}} \sum_{t=0}^{T} ((dis_{k,t}^{DA} - ch_{k,t}^{DA}) \cdot \sum_{s}^{S} (\pi_{k,s} \cdot \lambda_{k,s,t}^{DA}) \quad +$$

$$f_t^{\uparrow} \cdot \sum_{k}^{K} \pi_k \cdot \lambda_{k,t}^{flex\uparrow}) - (f_t^{\downarrow} \cdot \sum_{k}^{K} \pi_k \cdot \lambda_{k,t}^{flex\downarrow}) \; +$$

$$\sum_{s}^{S} \sum_{k}^{K} (\pi_{k,s} \cdot \lambda_{k,s,t}^{ID_{avg}} \cdot (dis_{k,s,t}^{ID} - ch_{k,s,t}^{ID})) + \sum_{s}^{S} \pi_{k,s} \cdot (-dev_{k,s,,t}^{\uparrow} \cdot \lambda_{k,s,t}^{BM,\uparrow} - dev_{k,s,,t}^{\downarrow} \cdot \lambda_{k,s,,t}^{BM,\downarrow})$$

$$- \underset{b_{s,k,t}}{\text{Max}} \sum_{s} \sum_{t} \pi_{k,s,t} (ch_{k,s,,t}^{ID} - dch_{k,s,t}^{ID}) \cdot \delta\lambda_{k,s,t}^{ID} \cdot b_{k,s,t}$$

$$s.t. \sum_{t} b_{k,s,t} \leq \Gamma, 0 \leq b_{k,s,t} \leq 1, \qquad \forall \text{s, k, t} \qquad (21)$$

By comparing the R-DLFM setup cost function (1) and the P-DLFM cost function (21), there are two major differences: i) Information availability for the DAM and the x-DLFM differs, and ii) probability coefficients differ. The DAM is in the starting point of the R-DLFM stochastic tree, hence the DAM price probabilities include only the first branching π_s, while the R-DLFM price is dependent on the first and second branching. In the P-DLFM setup, the situation is opposite and P-DLFM is at the starting point, hence the flexibility prices have probabilities π_k, while the DAM prices depend on two levels of branching, represented by $\pi_{k,s}$. Figure 24 depicts the chronological market clearing times in the P-DLFM setup. By comparing figures 22 and 24 it is easy to notice how different information availability affects the potential market actions. For instance, in the P-DLFM setup, the flexibility up and down variables are optimized without any price information, and they fit all future possible scenario realizations, while in the R-DLFM case the flexibility up and down variables are optimized after the DAM clearing. Thus, for each realization of the DAM price scenario, different values of flexibility variables are calculated. The IDM and BM are in fact the same in both market setups regarding the availability of information because the DAM and flexibility market prices are always known prior to the IDM and BM actions. For the sake of brevity, we assume that figures 22 and 24 alongside constraints listed in the section in the

Table 1 generate enough information so the reader may understand also the P-DLFM formulation. The main and only difference lies in the temporal dependency between the consequent market clearing times. The differences between two setups are analysed in a more detailed manner in the following subchapter.

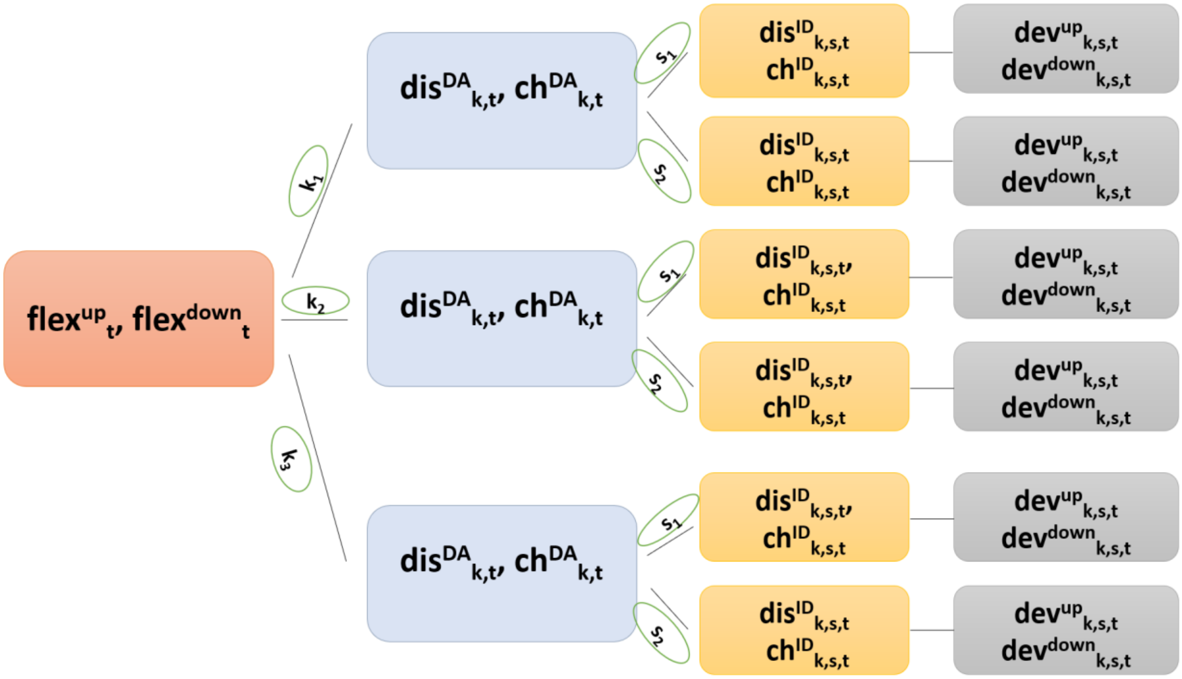


Figure 23 - P-DLFM concept decision stages

3.5 Performance evaluation results

3.5.1 General setup and input data

The Republic of Croatia was chosen for the case study for a number of reasons. First, as Croatia heavily relies on tourism (especially coastal parts), the number of people staying on islands increases by more than a factor of two comparing the winter and summer season. This results in considerable differences in power demand (both because of the number of inhabitants and the weather conditions) and different network capacity requirements. Considering the business-as-usual, without some type of flexibility market, the local distribution system operator is forced to oversize the network capacity with respect to the winter needs, so the power demand during the peak summer hours can be met. Second, Croatia was chosen because of availability of the DAM, IDM and BM prices. However, the DLFM does not yet exist in Croatia, so the prices were manually generated. The DAM and IDM price from the Croatian Power Exchange (CROPEX) are used, while the BM prices are based on the current regulations in Croatia and they were fetched from the ENTSO-E Transparency Platform. The same market data and battery characteristics are used for both the R-DLFM and P-DLFM setups. Table 2 summarizes the input prices for the DAM, IDM, BM and DLFM. The DAM, BM and DLFM use two price scenarios each. Although the model is computationally highly tractable, we opt for a low number of scenarios to better illustrate the mechanics of the model and better illustrate the results. The likelihood of occurrence of each scenario at the first level of branching is the same, i.e. in the R-DLFM market setup each DAM price scenarios has 50% probability, while in the P-DLFM case the same principle is valid but for the PDLFM prices, as P-DLFM is chronologically the first market to be cleared. In the second stage, further scenarios do not have the same probabilities. The price scenarios closer to the prices from the previous stage have 80% probability, while the other scenario has 20%.

The third market in chronological order is the IDM, which is not modeled via scenarios, but using an uncertainty range, i.e. all prices in between the upper one and the lower one can occur. The occurrence depends on the preset uncertainty budget. In the final stage, the BM prices are a direct consequence of the realized DAM prices. The considered battery storage has 5 MWh / 5 MW capacity. The round-trip efficiency is 0.81. Regarding the flexibility needs listed in Table 3, the distribution system needs to procure either upward or downward flexibility, as both directions are never needed at the same time. Positive values indicate the upward flexibility need, while the negative ones are for the downward flexibility request.

Table 2 - Prices in different markets [€/MWh]

Hour Market	1	2	3	4	5	6	7	8	9	10	11	12
DAM	22.75 47.08	39.5 46.46	19.03 44.65	23.95 45.59	39.93 46.27	39.5 53.22	60.33 65.09	67.0 78.22	75.7 76.73	72.62 64.63	69.58 62.12	67.89 55.16
IDM	31.7 48.85	28.16 49.93	24.79 47.3	24.0 47.59	27.0 48.23	45.0 51.67	63.76 64.03	77.96 76.23	81.0 78.22	88.91 71.06	105.93 64.44	80.33 54.1
BM↑	13.71 61.5	55.54 61.53	11.47 58.81	14.43 61.11	24.06 60.76	23.8 69.67	36.36 87.7	46.65 105.67	53.03 101.58	102.12 650.01	93.03 81.3	40.91 72.58
BM↓	13.71 61.5	55.54 61.53	11.47 58.1	14.43 61.11	24.06 60.76	23.8 69.67	36.36 87.7	46.65 105.67	53.03 101.58	102.12 650.01	92.03 81.3	40.91 72.58
DLFM↑	29.58 61.20	51.35 60.40	24.74 58.05	31.14 59.27	51.91 60.15	51.35 69.19	78.43 84.62	87.1 101.69	98.41 99.75	94.41 84.02	90.45 80.76	88.26 71.71
DLFM↓	18.2 37.66	31.6 37.17	15.22 35.72	19.16 36.47	31.92 37.02	31.6 42.58	48.264 52.07	53.6 62.58	60.56 61.38	58.10 51.70	55.66 49.70	54.31 44.13
Hour Market	13	14	15	16	17	18	19	20	21	22	23	24
DAM	65.65 49.7	63.91 45.92	63.6 43.04	63.43 43.08	62.59 52.76	61.24 59.52	63.46 64.03	70.05 82.37	71.44 77.01	62.41 67.04	62.97 65.69	60.72 60.0
IDM	90.92 49.66	80.45 42.32	56.99 42.76	64.15 44.59	61.46 48.74	63.45 53.22	84.04 59.53	83.67 69.28	89.63 69.68	70.65 68.2	69.79 65.74	67.16 60.32
BM↑	92.31 65.19	89.87 60.59	89.43 57.0	89.19 60.58	82.84 71.75	79.96 78.55	89.23 84.03	95.39 115.83	93.7 106.69	37.61 90.28	37.95 87.18	36.59 81.13
BM↓	92.31 65.19	89.87 60.59	89.43 57.0	89.19 60.58	82.84 71.75	79.96 78.55	89.23 84.03	95.39 115.83	93.7 106.69	37.61 90.28	37.95 87.18	36.59 81.13
DLFM↑	85.35 64.61	83.08 59.70	82.68 55.95	82.46 56.00	81.37 68.59	79.61 77.38	82.50 83.24	91.07 107.08	92.87 100.11	81.13 87.25	81.86 85.40	78.94 78.0
DLFM↓	52.52 39.76	51.13 36.74	50.88 34.43	50.74 34.46	50.07 42.21	49.00 47.62	50.77 51.22	56.04 65.90	57.15 61.61	49.93 53.63	50.38 52.55	48.58 48.0

Table 3 - Flexibility needs in the DLFM

h	1	2	3	4	5	6	7	8	9	10	11	12
MW	-2	5	0	-4	0	7	9	0	12	-4	0	4
h	13	14	15	16	17	18	19	20	21	22	23	24
MW	1	0	-7	0	6	0	2	-7	0	0	1	0

3.5.2 Model validation

The R-DLFM and P-DLFM market setups are modelled in the same manner to make comparable results. Depending on the chosen budget of uncertainty in the IDM, activities in markets change and, consequently, overall profits differ. Prior to the analysis on how different Γ values affect the battery storage's strategy and revenue, the models' validation and explanation is conducted with the value of budget of uncertainty zero, i.e. perfect foresight of the expected IDM trading success. Figures 25 and 26 show the battery's state of energy (SOE) and net charging/discharging activities for both market setups. The battery starts and ends the observed time horizon with the same SOE for all scenarios due to constraint (16). Figure 25 illustrates only the net battery activity described with the equation (10) that summarizes all market activities, so a more in-depth analysis of the activities in

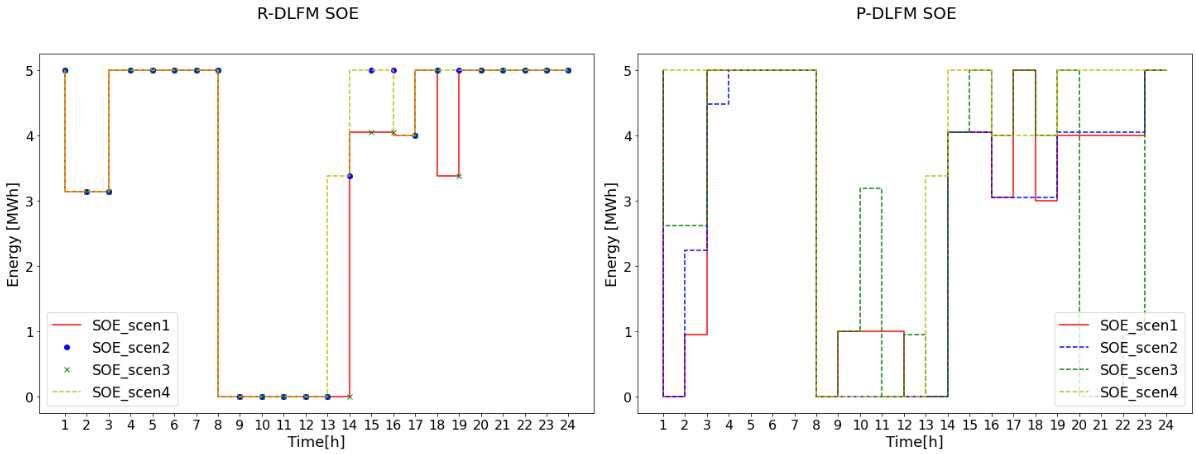


Figure 24 - State of energy during the observed time horizon with Γ = 0

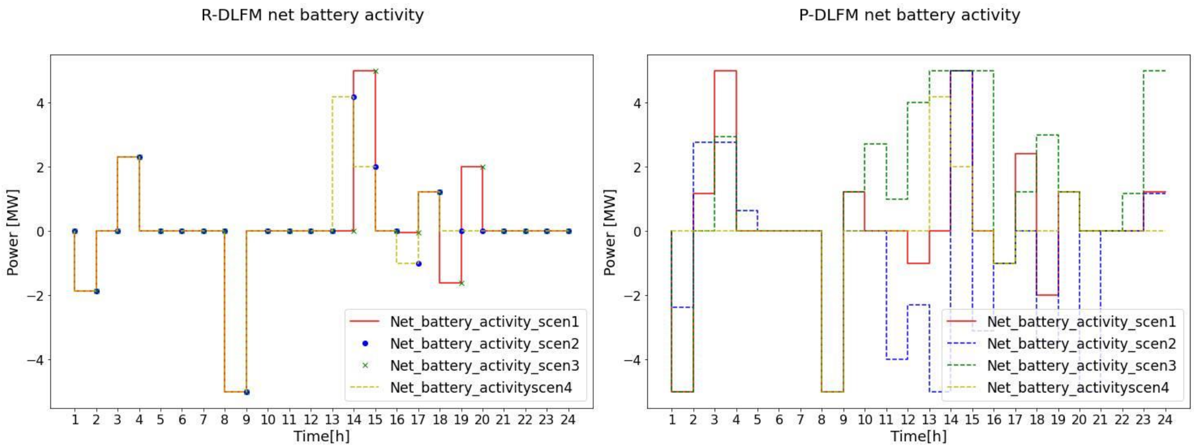


Figure 25 - 5. R-DLFM and P-DLFM battery activity (charging and discharging during the observed time horizon with Γ = 0)

different markets is needed to explore the arbitrage between markets within the same time periods. For the R-DLFM market setup, in all scenarios the battery is charged in hour 3, whose prices in all markets and scenarios are at the lower range as compared to the rest of the hours (see Table 1). In the same manner, the battery storage takes advantage of the high energy prices in all markets and discharges the battery in hour 8. Until the end of the day, the battery operation scheme follows the described strategy. Although in some hours the battery SOE stands still (it is constant), energy arbitrage between different markets produces profit and is conducted in a way that the amount of energy purchased in one market equals the energy sold in another. Inter-market arbitrage is highly beneficial for the battery as it does not incur any energy loss due to roundtrip inefficiency nor it degrades the battery capacity. Regarding the P-DLFM market setup, the same principles are valid as in the R-DLFM case but with the major difference that the P-DLFM clearing precedes the DAM clearing. Hence, the battery storage operator has different information availability and stochastic scenario tree structure, which leads to a somewhat different SOE profile. In the P-DLFM case, the battery's physical activity is much more expressed and there is a larger discrepancy between the scenario schedules than in the R-DLFM setup (graphs to the right in Figures 25 and 26). This is related to the fact that the P-DLFM prices are very attractive in comparison to the other markets, so as this market clears first, the battery storage operator's optimal strategy is to physically charge and discharge the battery exploiting the price differences within the DLFM market, while inter-market arbitrage is secondary source of revenue. To examine the process of energy arbitrage deeper, Figures 27 and 28 focus on only one stochastic tree branch in the RDLFM market setup with the Γ value set to 0. Scenario [0,0] includes the high DAM, IDM, BM and R-DLFM prices listed in Table 1. The prices in all markets in Figure 27 follow the same trend, but with different amplitudes and ranges.

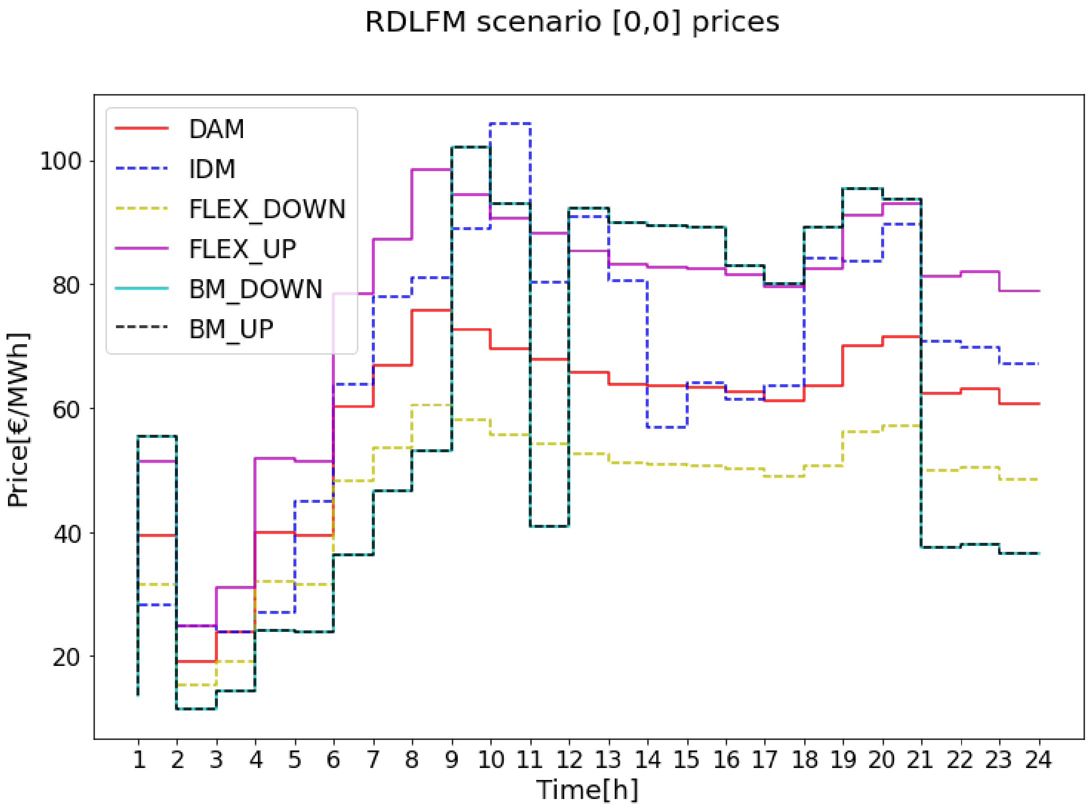


Figure 26 - Prices in different markets for scenario [0,0]

In terms of arbitrage, hour 5 clearly demonstrates the intermarket arbitrage. The overall net battery activity equals 0, however, an arbitrage is happening between the DAM and the IDM. In hour 5, the IDM price is 27 C/MWh, while in the DAM 39.93 C/MWh (48% higher than the IDM price!). Figure 28 indicates that in hour 5 maximum charging is performed in the DAM and maximum discharging in the IDM. Thus, the profit is achieved without even physically using the battery. The DAM can be used in R-DLFM to provide larger capacity in the DLFM. In hour 9 the net battery activity results in the maximum discharging power, i.e. 5 MW, motivated by the flexibility up demand. As the SOE cannot go under 0, the DAM was used to acquire enough energy so the battery can participate in the R-DLFM with 10 MW, which is double its power capacity. Thus, the up flexibility is achieved by cancelling the charging process at 5 MW scheduled in the DAM and instead discharging the battery at 5 MW. The described actions in hours 5 and 9 indicate that battery storage gains major benefit by acting in different markets and performing inter-market arbitrage, which generates a significant profit and results in trading power capacities higher than the actual battery capacity.

Purchasing energy in one market and then selling it in the other may result in zero, or at least lowered, actual battery charging/discharging, which extends the battery's lifetime. In other words, the battery operator sells energy in a market with higher price, while it buys it in the market with lower price in the same time period. Different scenarios bring different price relationships (differences) between markets, but in the end, the model follows exactly the same principles as shown in this example.

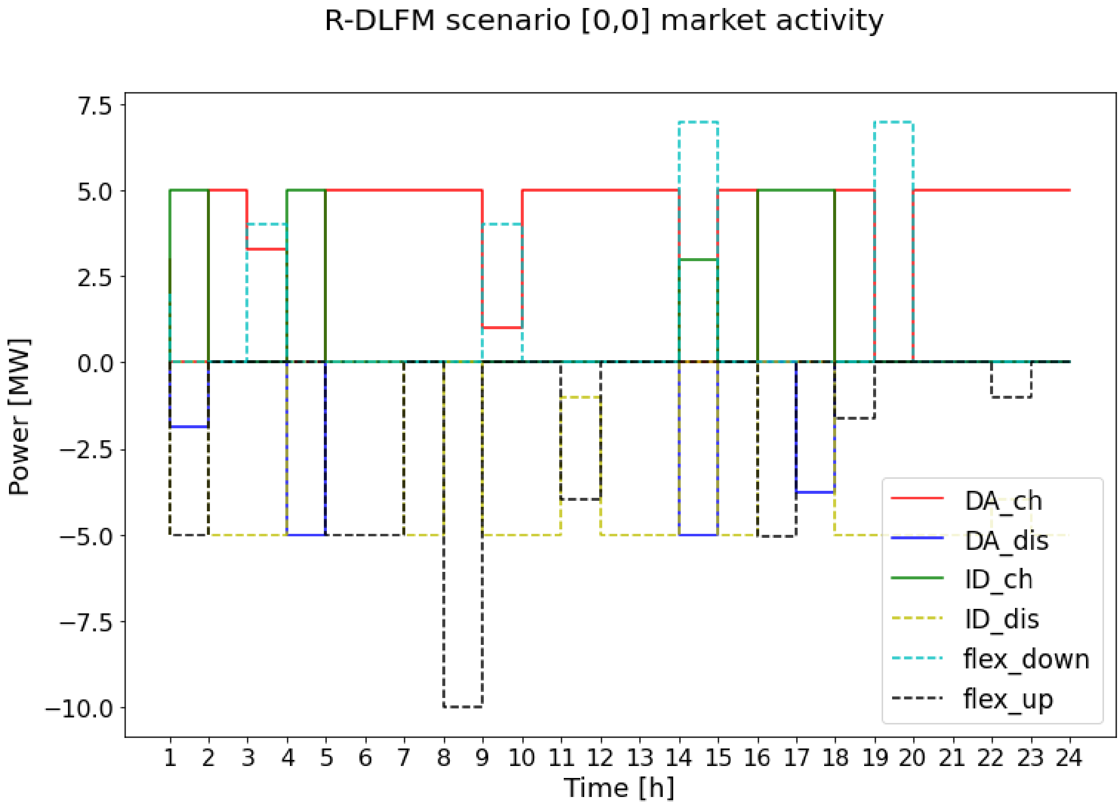


Figure 27 - Market activity for scenario [0,0] (positive values represent battery storage charging)

3.5.3 Uncertainty budget analysis

Figures 29 and 30 show that the battery storage's expected profit decreases with the increase of the uncertainty budget, i.e. as the IDM prices during more time periods are damaged by the robust optimization. More specifically, the IDM prices are less favourable when both buying and selling energy, thus effectively reducing the battery storage actions in this market. Due to the reduced profit opportunities, the overall profit also reduces with the increasing values of the uncertainty budget. Having in mind that the same data set was used in both market setups (R-DLFM and P-DLFM), it is highly interesting to notice that the P-DLFM setup generates higher overall profits for the profit-oriented battery storage. For $\Gamma = 0$, the R-DLFM profit is 1518€, while for the PDLFM 1589€ (4% higher profit). Although R-DLFM has the perk of easier integration into the existing power market structure, the P-DLFM setup has higher economic benefits to independent battery storage. This should be considered when opting for one of these two setups to be implemented in real-life systems. The maximum value of the uncertainty budget is 24, i.e. all of the observed hours are then affected by unfavourable IDM prices. In that case, the profit in the RDLFM sinks to 1079€ (29 % decrease compared to the case when $\Gamma = 0$) and to 1148€ in the P-DLFM (28 % decrease compared to the case when

Γ = 0). Furthermore, comparing the R-DLFM and P-DLFM market setup when Γ = 24, somewhat above 6% is higher profit for battery storage is achieved in the latter market setup. Next, we analyse the behaviour of the battery storage in the DAM and the IDM for both market setups. Figure 31 illustrates similar trends both for the R-DLFM and the P-DLFM setups. As the uncertainty budget increases, the overall discharged, i.e. sold, energy in the IDM decreases because the prices are becoming less favourable. The expected energy sold in the IDM in the R-DLFM setup throughout the day decreases from 71 MWh for Γ = 0 to 30 MWh for Γ = 24 (decrease of around 58%). In the P-DLFM setup the energy discharged in the IDM decreases from 61 MWh for Γ = 0 to 31 MWh for Γ = 24 (decrease of around 50%). Thus, for Γ = 0 the battery storage participates with higher amount of energy in the IDM in the R-DLFM case than in the P-DLFM case, however, the DAM charging (buying) activities are pretty similar (R-DLFM: 82 MWh, P-DLFM: 83 MWh). This is in line with the results presented in Figure 26 and the thesis that the inter-market arbitrage is much more emphasized in the R-DLFM setup. Furthermore, the DAM charging activity decreases in both cases with increasing uncertainty budget. In the R-DLFM setup the decrease is from 82 MWh to 55 MWh (33%), while in the P-DLFM setup the decrease is from 83 MWh to 61 MWh (27%). These results demonstrate that the effect of unfavorable IDM prices is more detrimental to the R-DLFM arbitrage strategy. Also, the IDM charged energy sinks in the R-DLFM setup from around 21 MWh to 14 MWh (33% decrease), while in the P-DLFM setup the reduction is from 25 MWh to 19 MWh (24%). One of the most important reasons why markets may face such notable decline in the battery activities for higher Γ values is the fact that the battery does not have any lower bounds on the energy that it has to deliver, so the battery operator strictly follows the strategy that brings the highest profit without any obligations besides the reported charging/discharging schedule. The DA discharging in both cases increases with the higher budget of uncertainty for over 30%. When it comes to the battery activity in the DLFM markets, Figures 32 and 33 show that P-DLFM setup stimulates higher utilization of flexibility service in comparison to the R-DLFM, regardless on the IDM uncertainty budget. Hence, when designing a new market structure, the trade-off will be between the ease of the integration (R-DLFM) and more intense activities in the local flexibility markets (P-DLFM). For both market setups the battery storage participation in the DLFM is inelastic to the values of the uncertainty budget, i.e. both up and down flexibility provision is (almost) identical regardless on the value of Γ. Very attractive DLFM prices used in this case study are the main reason for the battery storage's interest in the DLFM. However, comparing the RDLFM and P-DFM market setups, both flexibility up and down service provision is at least double in the P-DLFM market setup than in the R-DLFM, although the demand and prices are the same in both cases. Moreover, out of the total demand, the expected up flexibility service provided by the battery storage in the R-DLFM setup is 41%, while in the PDLFM setup it accounts for 83%. The explanation for this is that the P-DLFM precedes all the other markets. For completeness, we mention the battery storage activity in the BM. Both for the R-DLFM and P-DLFM setups the battery activity is zero. The BM costs are so high that by all means in both market setups the battery storage tries to avoid the BM corrections to its market position. However, if the DLFM prices would increase, the battery storage operator might receive an incentive to deviate. We conclude the case study with graphs that depicts the overall charging and discharging activities depending on the uncertainty budget. Figure 34 shows the overall charged and discharged energy quantity during the day for all possible values of the uncertainty parameter Γ in the R-DLFM and P-DLFM setups. There is a constant difference between the charging and the discharging quantities in the graphs due to battery inefficiency.

In the R-DLFM graph there is no clear trend to relate the charging/discharging energy and the budget of uncertainty. On the other hand, in the P-DLFM setup, an increase in the Γ value results in reduced physical charging/discharging energy.

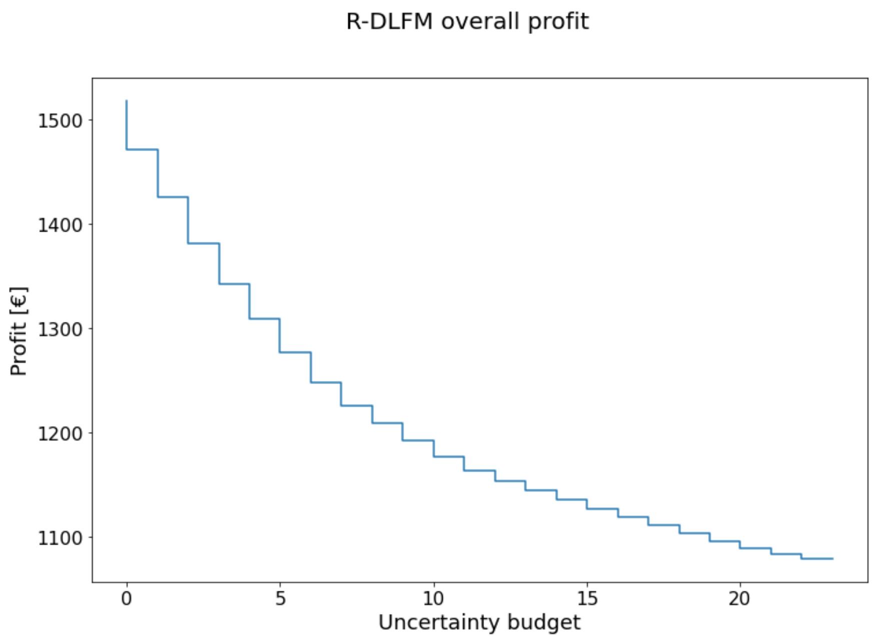


Figure 28 - Overall expected profit vs uncertainty budget in the IDM for R-DLFM

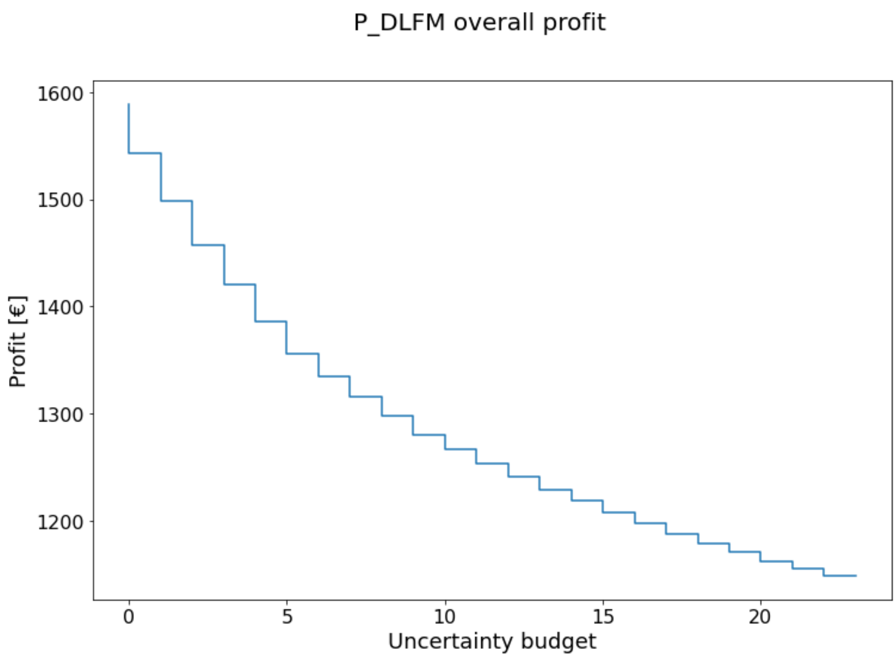


Figure 29 - Overall expected profit vs uncertainty budget in the IDM for P-DLFM

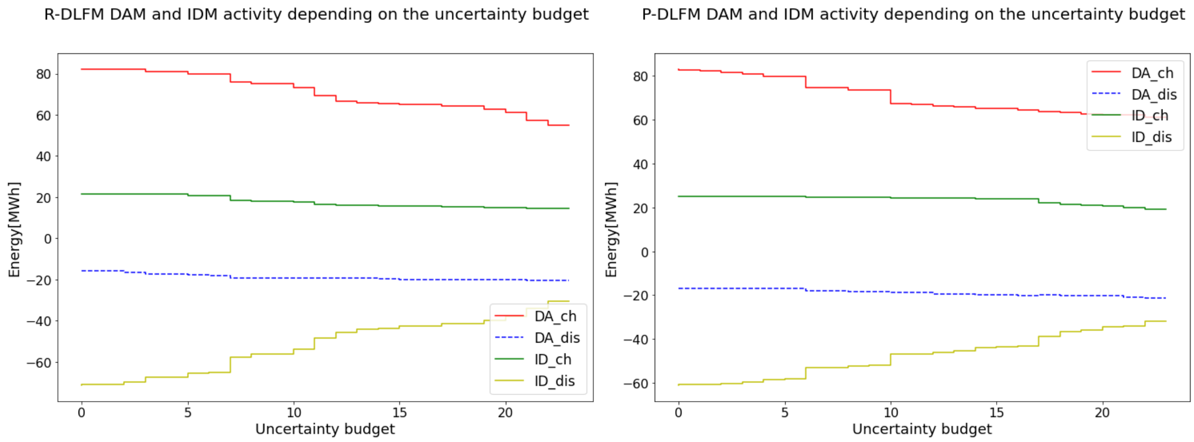


Figure 30 - DAM and IDM activity for R-DLFM and P-DLFM market setups in regards to the value of the uncertainty budget in the IDM

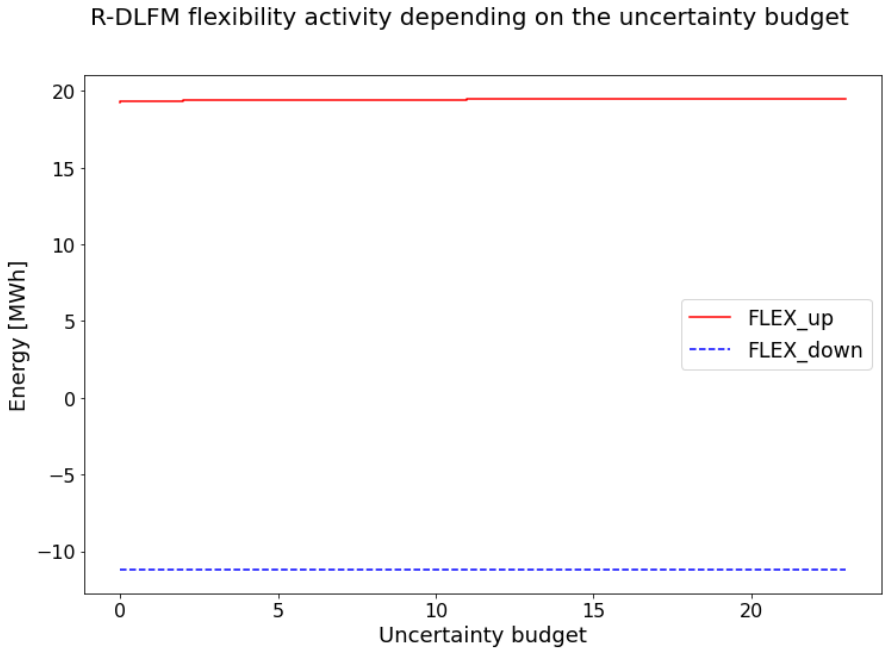


Figure 31 - Flexibility actions vs uncertainty budget R-DLFM

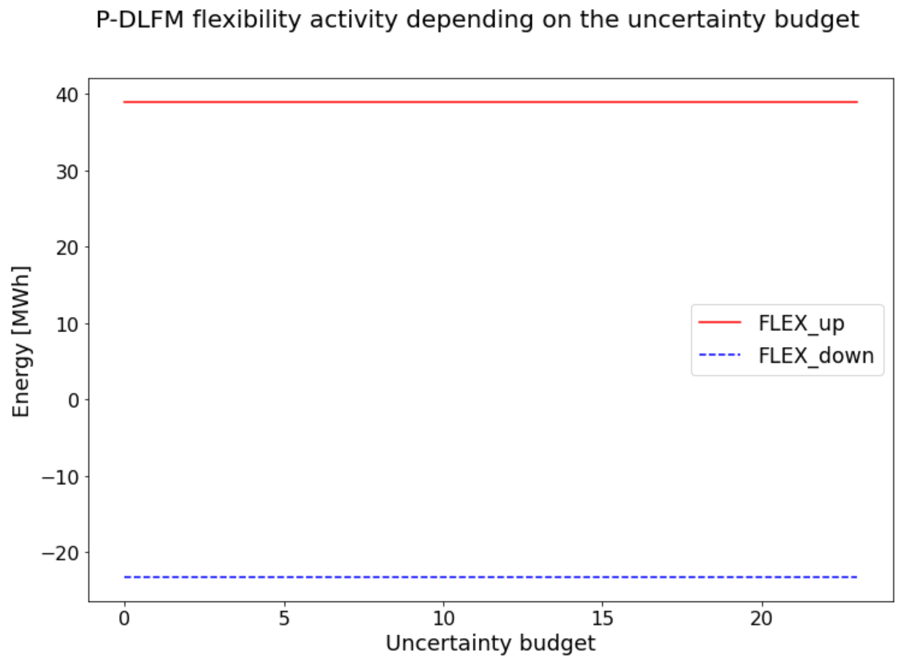


Figure 32 - Flexibility actions vs uncertainty budget P-DLFM

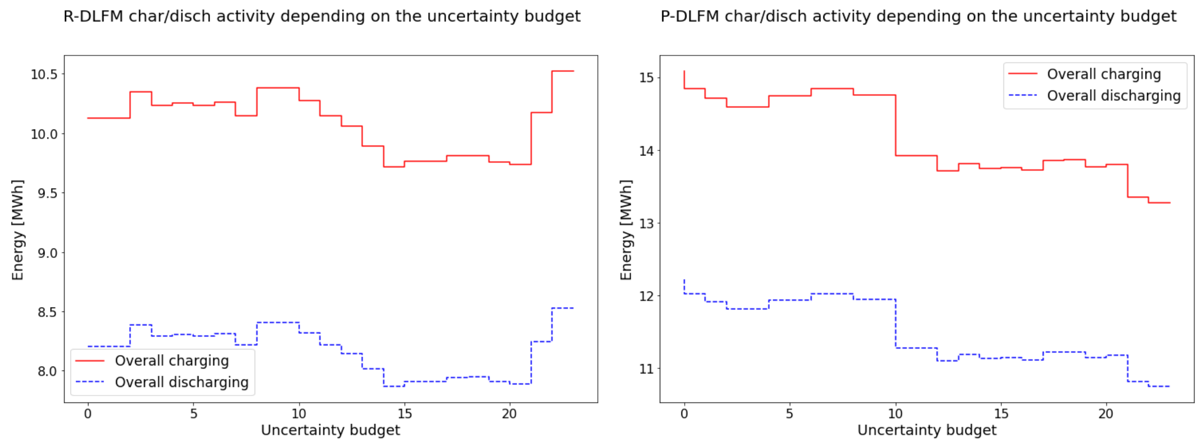


Figure 33 - R-DLFM and P-DLFM charging and discharging activity depending on the uncertainty budget

3.6 Lessons learnt and roadmap towards Horizon Europe 2021-2027

Focus of interest in the FLEXGRID UCS 2.1 is the development of a scheduling algorithm that results with lower OPEX for a profit-oriented ESP, considering existing markets and the proposed DLFM. To make the model truly credible, special attention has been given both to the uncertainty and battery modelling. Different markets have different clearing characteristics, hence different uncertainty aware techniques have been used – stochastic optimization for pay-as-clear systems and robust optimization for the case where trading is conducted continuously. Two types of DLFM were addressed as part of the FLEXGRID UCS 2.1. The R-DLFM is cleared between the DA and the ID markets, while the P-DLFM precedes the DAM. According to current legislative situation, R-DLFM is certainly a better fit to the current power market structures concerning the complexity of integration. But the question was also which market setup would ESP potentially benefit from the most. Analysing these two market setups, P-DLFM provides greater profit potential to the respective profit-oriented player. An important factor that also needs to be explored in detail is the price formation for the flexibility market. Nonetheless, the developed model helps the profit-oriented ESP to increase its profit and exploit the benefits offered by the wide variety of currently active markets and potential ones at the distribution level. Throughout the whole process, many questions have been raised, many models have been analysed and we attach short list of lessons learnt that have potential for further investigation in some future R&I initiatives.

Table 4 - Lessons learnt for UCS 2.1

Lesson learnt	Research & Business insights
R-DLFM is the “best-fit” to the existing market structure, but other market setups may result to greater benefit for a profit-oriented ESP	Although R-DLFM seems like the best option when considering the potential solutions for the creation of the distribution level market, important factor to consider is also what entities and in what volume do benefit from different market structures. Because, for a potential distribution level market to be even considered by industry, involved partners should have a financial initiative to be involved in something new. Hence, both FLEXGRID and future projects need to decide the optimal solution considering all factors.
Need for precise battery modelling	The value of proposed scheduling algorithm may be heavily impacted by unreliable battery modelling techniques. Moreover, wherever battery storages are used, precise state of energy dynamics is of a great importance for the results. Hence, as part of this UCS, advanced battery modelling technique was used, but research should be conducted also in the future. Perhaps even more precise modelling techniques may be developed.
Attractive flexibility prices may overcome market architecture dilemmas	The results have shown that, depending on the flexibility market prices, although overall ESPs’ benefit may differ, activity in the flexibility market may be pretty much consistent. Hence, should the decision makers opt for the R-DLFM due to integration simplicity, emphasis should be given to the price formation. Nevertheless, further research should investigate price formation possibilities and mechanisms.
Scope of the markets included in the model changes the perspective	UCS 2.3 has included three existing markets in addition to the proposed x-DLFM. Further research should perhaps broaden the scope and then analyze the trade-off between the

	computational (and modelling) burden and credibility of results.

4 ESP's CAPEX minimization problem (UCS 2.2)

4.1 Introduction

The focus of this chapter is the research problem of the FLEXGRID's HLUC#2 UCS#2 (HLUC02_UCS_02). We consider a profit-seeker Energy Service Provider (ESP) as the main subject of the capital expenditures (CAPEX) optimization problem. To optimize CAPEX, the ESP needs to conduct optimal investments on RES and FlexAssets, both in terms of siting and sizing. The holistic network-aware approach takes into consideration:

- Various electricity markets
- Network topology and constraints or DSO's zone approach as in the NODES example
- Detailed study of various battery types (their characteristics such as charging/discharging efficiency, etc.)
- RES generation forecasts
- Market price forecasts

Respecting the given objective function (e.g. 5% operational expenditure (OPEX) reduction), the optimal siting and sizing algorithm ensures the optimal investment strategy.

4.2 Problem statement and summary of FLEXGRID research contributions

Optimal CAPEX strategy may present important comparative advantage over the rival companies. Furthermore, optimal resource allocation may benefit the overall social welfare, assuming that the greater competition raises market efficiency and that the greater number of players will have the opportunity to enter the market and increase the competition with each other. In that sense, a profit-seeker ESP, whose portfolio may consist of various controllable and uncontrollable assets, uses CAPEX minimization tool to determine optimal investment strategy in terms of: i) size and ii) location of the different assets to fulfil its own goals and network requirements. Within FLEXGRID project's context, optimal sizing and siting algorithm is used to ensure optimal investment strategy considering the given constraints and the objective function. In addition to the existing markets, the development of a DLFM is proposed and its influence on ESP's market behaviour alongside the conventional power markets is observed. Taking into account possible actions on all of the observed markets (DAM, RM, DLFM and BM), CAPEX minimization algorithm proposes the optimal investment strategy to participate in the energy market(s) in a preferrable fashion. Meaning that for a specific one-time capital investment, operational expenses may be reduced.

4.3 System Model

This work proposes a market architecture in which DLFM follows the clearing process of the DAM and RM, without changing the existing transmission-level wholesale market structure (as shown in the figure below). Although the emphasis is on the investment in new FlexAssets, as CAPEX strategy is highly OPEX dependent, so the market behaviour also needs to be modelled. Thus, it is important to explain the proposed market structure. The ESPs will need to balance their portfolio on the BM if by participating in the DLFM they alter dispatch of the TSO-level markets. In this context, an ESP may participate in all the aforementioned markets under the Reactive DLFM (R-DLFM) architecture model. Figure 35 clearly illustrates how Reactive DLFM (R-DLFM) fits with the existing EU regulatory framework. That is the main reason why is the R-DLFM considered, and why it was decided to implement UCS 2.2 until TRL 5 via the deployment of FLEXGRID ATP. The sequence of the existing markets remains as is and no regulatory changes are required. The only new market is the DLFM, which reacts to the dispatch decisions made by the previous DAM and RM in order to deal with the distribution-level related problems such as local congestion and voltage control issues. Figure 35 shows the clearing sequence of the mentioned markets, interaction between them entities and transmission/distribution level that are in regards with them. More technical details are provided in chapter 5.

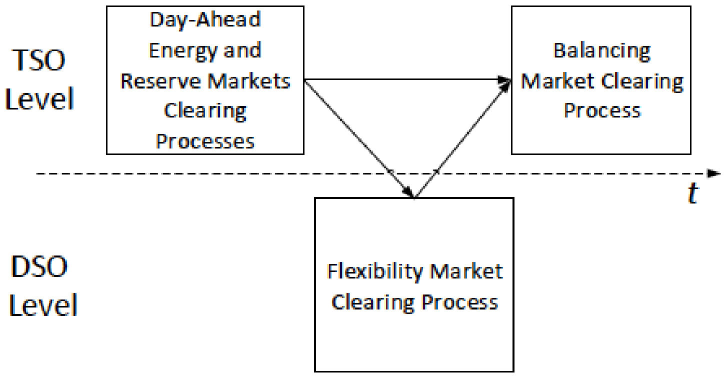


Figure 34 - Proposed system model of the UCS 2.2

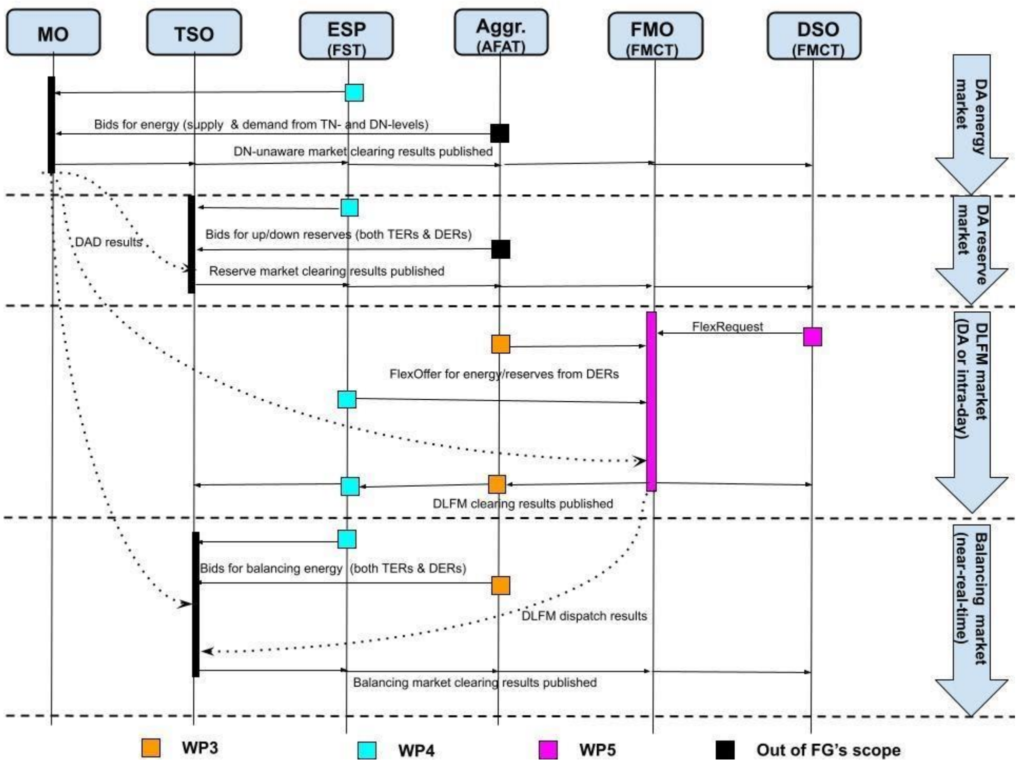


Figure 35 - Placement of UCS 2.2 mathematical model and algorithm in the Reactive DLFM architecture proposed by FLEXGRID

4.4 Problem Formulation

The ESP's CAPEX minimization problem is modelled as a single-level optimization problem with network constraints taken into account. The ESP wants to reduce its day-to-day operational costs by investing in new FlexAssets. More precisely, the CAPEX is highly dependent on the given OPEX reduction goals (e.g. 5%). The model is network aware, but with the important notice that the ESP's accessibility to the underlying network data may vary according to the will of the DSO and/or the regulatory framework constraints. In that manner, we greatly rely on NODES'[3] zone approach technique, where the whole distribution zone is divided into multiple zones and with relevant information (input data) revealed to the ESP. Due to somewhat longer period of formulating the final algorithmic solution and computational issues that are still to be resolved with model reformulations, here is presented the optimal battery storage siting and sizing solution but without concerning the possibility of market participation. Should the ESP have the complete insight into the network topology, the following constraints model the AC optimal power flow using the Branch Flow Model (BFM) with (1) as the objective function:

$$\underset{\omega}{\text{Min}} \sum_{t=0}^{T} \sum_{i}^{N} \sum_{j \neq i}^{N} \left[\left| p_{ij,t} + p_{ji,t} \right| \cdot \lambda^{loss} \right] + \sum_{i}^{N} soe_i^{max} \cdot \lambda^{batt} + \sum_{t=0}^{T} \sum_{i}^{N} p_t^{gen} \cdot \lambda^{gen} , \quad \forall t, i, j \quad (1)$$

$$p_{ij,t} = \left[r_{ij} \cdot I_{ij,t} - (p_{j,t}^{gen} + dch_{j,t} - p_{j,t}^{d} - ch_{j,t}) + \sum_{m:j \rightarrow m} p_{jm,t} \right], \qquad \forall t, i, j \qquad (2)$$

$$q_{ij,t} = \left[x_{ij} \cdot I_{ij,t} - q_{j,t} + \sum_{m:j \rightarrow m} q_{jm,t} \right] + v_j \cdot \frac{b_{ij}}{2} , \qquad \forall t, i, j \quad (3)$$

$$v_{j,t} = v_{i,t} - 2 \cdot \left(r_{ij} \cdot p_{ij,t} + x_{ij} \cdot q_{ij,t} \right) + I_{ij,t} \cdot \left(r_{ij}^2 + x_{ij}^2 \right) , \qquad \forall t, i, j \qquad (4)$$

$$I_{ij,t} \geq \frac{p_{ij,t}^2 + q_{ij,t}^2}{v_{i,t}} , \qquad \forall t, i, j \quad (5)$$

$$p_{ij,t}^2 + q_{ij,t}^2 = S_{ij,t}^2, \qquad \forall t, i, j \quad (6)$$

$$q_{i,t} = \sum_{g} q_{i,t}^{gen} - \sum_{d} q_{i,t}^{d} , \qquad \forall t, i \quad (7)$$

$$P_i^{gen,min} \cdot x_t^{gen} \leq p_{i,t}^{gen} \leq P_{i,g}^{max} \cdot x_t^{gen}, \qquad \forall t, i \qquad (8)$$

$$Q_{i,t}^{gen,min} \cdot x_t^{gen} \leq q_{i,t}^{gen} \leq p_{i,g}^{max} \cdot x_t^{gen}, \qquad \forall t, i \qquad (9)$$

$$-S_{ij}^{max} \leq S_{ij,t} \leq S_{ij}^{max}, \qquad \forall t, i, j \quad (10)$$

$$v_i^{min} \leq v_{i,t} \leq v_i^{max}, \qquad \forall t, i, j \quad (11)$$

$$soe_{i,t_0} = 0.5 \cdot soe_i^{max}, \qquad \forall t, i \quad (12)$$

$$soe_{i,T} = 0.2 \cdot soe_i^{max}, \qquad \forall t, i \quad (13)$$

$$ch_{i,t} \leq P_i^{ch,max} \cdot x_{i,t}^{batt}, \qquad \forall t, i \quad (14)$$

[3] https://nodesmarket.com/about/

$$dch_{i,t} \leq P_i^{dch,max} \cdot \left(1 - x_{i,t}^{batt}\right), \qquad \forall t, i \ (15)$$

$$soe_{i,t} \leq soe_i^{max}, \qquad \forall t, i \ (16)$$

$$soe_{i,t} = soe_{i,t-1} + ch_{i,t} \cdot \eta - \frac{dch_{i,t}}{\eta} \ , \qquad \forall t, i \ (17)$$

The objective function in its current form, which still needs to be updated when the computational issues are resolved, punishes losses $\left|p_{ij,t} + p\right|$ with the penalty factor λ^{loss}, accounts for the cost of investment in new battery storage unit according to its maximum capacity $soe_i^{max} \cdot \lambda^{batt}$ and includes also possible generation costs of the DERs installed in the respective distribution grid (e.g. ESP doesn't own them and needs to pay some fee) - $p_t^{gen}\lambda^{gen}$. The BFM relaxes the standard model and takes primarily into consideration power and electricity flow through branches. Constraint (2) models the active power flow between the nodes (including ohmic loss). Generating unit and battery storage unit in the discharging mode may inject energy into the system, while demand and battery storage unit in the charging mode present load. In similar manner constraint (3) models the reactive power flow. I_{ij} represents squared current value flowing through the branch ***ij***, $\boldsymbol{p_{ij}}$ denotes active power flow through the branch, p_j^{gen} is the generation in the node *i*, $dch_{j,t}$ denotes discharging power for the node *j*, whereas ch_j charging power and p_j^d demand. The last term in (2) depicts power flow going in the downstream direction. The notation in (3) follows the similar principle as (1), with the addition of shunt susceptance (last term). Constraint (4) determines the squared voltage ($v_{i,t}$) per each node. Constraint (5) in its exact form should be an equation rather than an inequality, but such formulation is non-convex, hence, generally speaking, unacceptable for today's solvers. So, the Second-Order Cone Programming (SOCP) has been introduced and equality relaxed to inequality which resulted with convex (conic-shaped) constraint. The constraint itself couples four variables: i) squared current, ii) active power flow, iii) reactive power flow and iv) squared voltage. Constraint (6) governs the relationship between active, reactive and apparent power. Constraint (7) sum active and reactive power and demand, because they are currently not separately represented in the equation (3) as it is done in the active power case in the equation (2). Constraints (8)-(11) define minimal and maximal allowed values for active power, reactive power, apparent power and squared voltage. Binary variable $x_{i,t}^g$ depicts whether a generator is operating (if it equals one) or is it turned off in the time unit *t*. Constraints (12) and (13) regulate state of energy (soe) for each battery storage unit in the initial time unit and minimum allowed soe at the end of the optimization horizon, respectively. (14) regulates the maximum charging power when battery is in the charging mode ($x_{i,t}^{batt} = 1$), in other case it cannot charge. Similarly, constraint (15) limits the battery discharging power when the battery is in the discharging mode, in other case it cannot discharge. Constraint (17) models the intertemporal dependency of the battery's state of energy – soe in the time unit *t* dependents on the soe in the time unit *t*-1 and charging/discharging of the battery in *t.*

Unfortunately, to complete the problem formulation and encompass participation in different markets, still some computational issues need to be resolved. Hopefully, all the problems will be resolved and fully operational siting and sizing algorithm will be integrated as part of the FST in the FLEXGRID ATP.

4.5 Algorithmic solution

The formulated linear single level problem should be solvable by almost any of the currently available solvers. At this stage, the potential problem would present non-convexity of the constraint (5) if it was equality. To ensure the convexity of the optimization problem, SOCP convex relaxation method was used and conic shaped area produced constrained by (5) replaced the non-convex shape which equality version of the constraint insists on. Furthermore, significant computational problems have been identified when participation in various markets had been included in the model. Hence, the presented problem formulation lacks market participation section, but the version integrated in the ATP FLEXGRID as part of the FST (TRL 5) will include all the vital functionalities and require reasonable computational effort. The final version of the objective function of the optimization problem penalizes both CAPEX and multiple OPEX scenarios (according to the capital investments). The algorithm reports optimal siting and sizing strategy to satisfy OPEX reduction target spending the minimum necessary amount of money on capital investments.

4.6 Lessons learnt and roadmap towards Horizon Europe 2021-2027

Focus of interest in the FLEXGRID UCS 2.2 is the development of an optimal siting and sizing algorithm that results with lower CAPEX for profit-oriented ESP, considering existing markets and the proposed DLFM. Although issues that are still to be resolved prevent us from presenting final results and detailed analysis how an ESP may invest in new FlexAssets to reduce its OPEX, the lessons learned along the way are of great value. Nonetheless, the model will be quickly developed in its full capacity, and as such it will be vital part of the FLEXGRID ATP FST. Throughout the whole process, many questions have been raised, many challenges have been encountered and addressed and we attach short list of lessons learnt that have potential for further investigation in some future R&I initiatives.

Table 5 - Lessons learnt for UCS 2.2

Lesson learnt	Research & Business insights
CAPEX and OPEX are highly dependent	When ESPs are creating their strategies, it is important to emphasize them how different magnitudes of investments in FlexAssets have impact on day-to-day expenses, and vice-versa. Hence, tools to compare different scenarios are indeed helpful for respective ESP to use their existing assets in optimal manner, take advantage of the possibility to participate in the electricity market and possibly invest in new FlexAssets to improve its market position.
Computational efficiency is of great importance	Models which include participation in different markets, network awareness and complex set of optimization variables may require high computational efforts to produce results. For practical usage, model should be easy to run on different computers, hence it is important to formulate a model that meets those requirements. Industry requires accurate and easy to

	run models, and this tool will present exactly that case. Future research could include also new features, but constantly taking in mind computational issues that may happen.
Deep interaction between FSP, DSO and TSO is needed. An advanced FSP-DSO-TSO interaction scheme needs to take place in order to achieve competitive, economically sustainable and network upgrade-aware investments of FlexAssets	ESP, DSO and TSO have conflicting interests, so a trade-off analysis needs to take place between sustainable DER investments and social welfare maximization. ESP-DSO-TSO interaction can achieve the optimum results compared to the case in which per actor investment decisions are made independently.

5 ESP's profit maximization by co-optimizing its participation in several energy and local flexibility markets (UCS2.3)

5.1 Introduction to the ESP's profit maximization business case

This chapter deals with the research problem of UCS 2.3. In FLEXGRID, we consider a profit-seeker Energy Service Provider (ESP), who owns a set of Battery Storage Units (BSUs) located at various nodes of a radial distribution network. In order to maximize its profits, the ESP may participate in several energy markets and dynamically optimize its bidding strategy. In more detail, it exploits: market price forecasts, energy prosumption forecasts and information on the underlying network topology in order to derive its optimal scheduling and bidding strategy towards maximizing its business profits. Without loss of generality, we assume the ESP's participation in four markets, namely:

- Day-Ahead Energy Market (DAM) operated by the MO,
- Day-Ahead Reserve Market (DA-RM) operated by the TSO,
- Day-Ahead Distribution-Level Flexibility Market (DA-DLFM) operated by a novel market entity introduced by FLEXGRID market architecture, called FMO, and
- Near-real-time Balancing Market (BM) operated by the TSO.

Within FLEXGRID project's context, we propose a novel energy market architecture that is called Reactive Distribution Level Flexibility Market (R-DLFM), which is compatible with today's EU regulatory framework. A Flexibility Market Operator (FMO) clears the R-DLFM by minimizing the cost of acquiring the flexibility needed to ensure the participation of the Distributed Energy Resources (DERs) in the wholesale markets without jeopardizing the reliable operation of the distribution network.

In this market environment, a merchant owner of Battery Storage Units (BSUs) can increase its profitability by providing energy and ancillary services at both the transmission and distribution level. BSUs with smart inverters can provide various valuable grid services to the TSOs and DSOs. In UCS 2.3, we consider an ESP as a market stakeholder, which owns a set of distributed BSUs and provides services to both the system-wide grid (TSO) and the local distribution network (DSO).

5.2 Problem statement and summary of FLEXGRID research contributions

In today's power sector in Europe, the procurement of flexibility is characterized by a monopsony, since the Transmission System Operators (TSOs) are the only buyers of such services. In addition, the interaction between the TSOs and the Distribution System Operators (DSOs) is insufficient and the clearing process of the wholesale energy markets does not take into account the distribution grid operation and associated constraints (cf. the problem of today's DN-unaware market clearing in EU area that is addressed by FLEXGRID WP5). Consequently, the participation of distributed generators (DGs) and other DERs in such markets can lead to violations of the physical constraints that the distribution network imposes and, consequently, to inefficient (technically and economically) market results. The latter dictates the need of a shift of the DSO's role towards a more active network operator, which should be entitled to purchase flexibility services from the local DERs.

Congestion management and frequency/voltage control issues caused by high and distributed RES penetration increase the volatility of energy prices in modern energy markets (TN-level) as well as in emerging local flexibility markets (DN-level). **This temporal and spatial volatility reveals the markets' characteristics and at the same time offers business opportunities and revenues for ESPs that invest in DERs.**

Taking into account the recent smart grid architectural progress in the development of distribution-level flexibility markets[4], this work co-optimizes the transmission and distribution grid services provided by an FSP owning distributed BSUs, using bi-level programming[5] [6]. By considering market scales, we assume that the FSP is acting as a price maker in the Reserve Market (RM) and the DLFM, while it cannot affect the market prices in the wholesale energy and balancing markets (i.e. acts as a price taker). Thus, the FLEXGRID UCS 2.3 research contributions can be summarized as follows:

- It proposes a novel energy market architecture, in which a DLFM is introduced in the timeframe between the day- ahead energy and the near-real-time balancing markets. An innovative DLFM clearing process is proposed, which enables the DSO to buy (i.e. FlexBuyer) the needed flexibility to tackle the possible contingencies resulting from the DN-unaware wholesale energy market dispatch decisions, calculating the optimal flexibility dispatch and compensation for the ESP (i.e. FlexSupplier).
- A new bidding strategy is proposed for an ESP that stacks revenues based on four products: 1) wholesale energy arbitrage, 2) reserve capacity and 3) balancing energy for the TSO, and 4) local constraint support for the DSO. Bilevel modeling is used to model the strategic participation of a BSUs' owner in both the TSO and DSO markets.
- A novel iterative process is proposed to deal with non-linearities due to the ESP's participation in two inter-dependent markets.

To the best of FLEXGRID consortium's knowledge, this is the first work that uses bi-level programming to model the decision process of a strategic ESP owning distributed BSUs and providing services both system-wide and to the local network operator. The interested reader may find more details about state-of-the-art related works from the international literature in D4.2[7].

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[4] Universal Smart Energy Framework (USEF), "Flexibility Platforms", November 2018. Available Online: https://www.usef.energy/app/uploads/2018/11/USEF-White-Paper-Flexibility-Platforms-version-1.0_Nov2018.pdf

[5] E. Nasrolahpour, S. J. Kazempour, H. Zareipour, and W. D. Rosehart, "A Bilevel Model for Participation of a Storage System in Energy and Reserve Markets", *IEEE Trans on Sustainable Energy*, vol. 9, no. 2, pp. 582-598, Apr. 2018.

[6] H. Pandzic, Y. Dvorkin, and M. Carrion, "Investments in merchant energy storage: Trading-off between energy and reserve markets", *Applied Energy*, vol. 230, pp. 277-286, 2018.

[7] H2020 FLEXGRID D4.2, https://flexgrid-project.eu/assets/deliverables/FLEXGRID_D4.2_final_31032021.pdf

5.3 System Model

This work presents a market architecture in which a Distribution Level Flexibility Market (DLFM) follows in an optimal way the decisions made by the DN- unaware day-ahead energy and reserve markets (intra-day timeframe), without changing the existing TN-level wholesale market structure being thus compatible with the existing regulatory framework. This Reactive DLFM (R-DLFM) architecture enables:

- the DERs to participate in the TSO wholesale markets without jeopardizing the smooth operation of their underlying network, and
- the DSO to buy the needed flexibility to remove contingencies resulting from the DN-unaware wholesale energy market dispatch process.

In a first step, as shown in the figure below, the Market Operator (MO) runs the Transmission Network (TN)-level day-ahead energy market after the TN-level Energy Service Providers (ESPs), such as generating companies, demand aggregators, retailers, etc., and the DN-level Flexibility Service Providers[8] (FSPs) have submitted their energy offers/bids.

Subsequently, the TSO operates the day-ahead reserve market given the MO's dispatch schedules (cf. Day-Ahead Market - DAM dispatch) and the reserve capacity offers from the Reserve Market (RM) participants. This practice is common in most European markets (e.g. Nord Pool, EPEX, OMEL, GME, MIBEL), where the energy and reserve markets are sequentially cleared[9]. The role of the RM is to provide to the TSO the required upward/downward reserve capacity to keep its system balanced in the real-time (balancing) stage.

In the third step, the distribution-level FSPs submit their flexibility offers (active and reactive up/down flexibility) to the FMO, which in turn clears the local DLFM, taking into consideration the DAM results, the particularities and the constraints of the DN (provided by the DSO), thus performing the DN- aware market clearing process. The role of the DLFM is to ensure that the DN operates within its safety/reliability limits, i.e. to remove local congestion, local balancing and voltage control issues that might occur due to the DN-unaware DAM clearing process. Thus, the FMO clears the DLFM by running an OPF problem, which takes as input:

- the MO's decisions pertaining to the local DERs that participate in the DAM,
- the active/reactive up/down flexibility offers submitted by the FSPs, and
- the DN constraints provided by the DSO.

In case the TN-level DAM has not produced dispatches that violate the DN constraints, the DLFM results in zero flexibility procurement and, of course, zero DLFM prices. Otherwise, the DLFM produces non-zero active/reactive and upward/downward flexibility dispatches and the corresponding flexibility prices per DN node at which the FSPs will be paid for providing their flexibility services. Therefore, the DLFM clearing process will re-adjust the DAM position of the DERs located in the specific DN. Thus, these DERs will have to balance their portfolio

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[8] We use the term FSP for the DLFM participation, because in R-DLFM architecture, we consider that active power reserve and reactive power reserve products (that provide flexibility services to the DSO) are traded.

[9] J. Iria, F. Soares, and M. Matos, "Optimal bidding strategy for an aggregator of prosumers in energy and secondary reserve markets", Applied Energy, vol. 238, pp. 1631-1372, Mar. 2019.

in the TSO's near-real-time balancing market (sell/buy power), in order to respect their commitment to the MO (DAM dispatches). For more details regarding the R-DLFM architecture, we kindly refer an interested reader to previous FLEXGRID reports, i.e. D2.2[10] and D5.1[11].

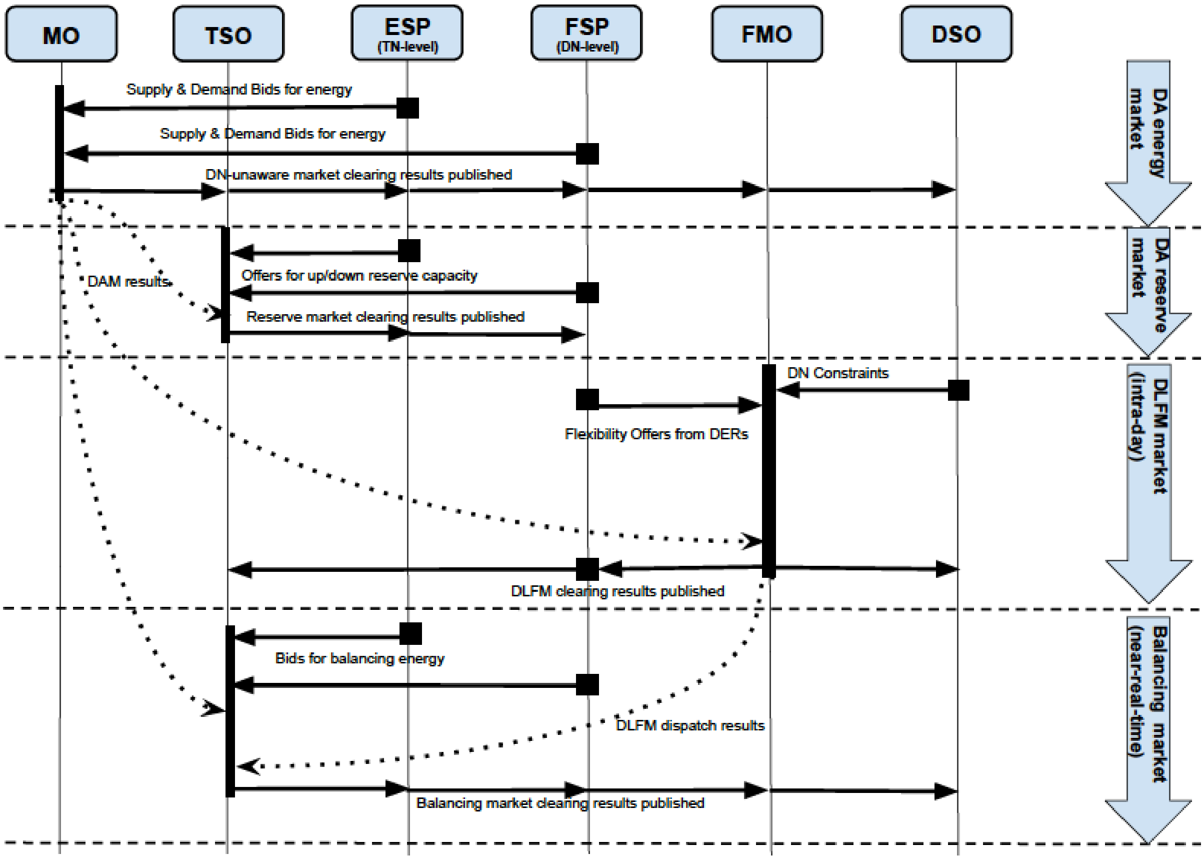

Figure 36: Proposed Reactive Distribution-Level Flexibility Market (R-DLFM) architecture

5.4 Problem Formulation

In the context of the proposed R-DLFM architecture, we propose a bidding strategy of a profit-seeking ESP that owns a set of BSUs located at various nodes of a radial DN and participates in the TN-level energy, reserve and balancing markets, as well as in the DLFM. We assume that the ESP/FSP cannot affect the DAM and Balancing Market (BM) prices (acts as a price taker), while its total BSUs' capacity is able to influence the Reserve Market (RM) and the DLFM prices. The objective of the ESP is to maximize its stacked revenues by optimizing its bidding strategy in the four aforementioned markets. The ESP submits:

- self-scheduling bids in the DAM and BM,
- price-quantity pairs for upward and downward reserve capacity in the RM, and
- price-quantity pairs for four products in the DLFM, i.e.:
  - upward active power (MW – euros/MW),
  - downward active power (MW – euros/MW),

[10] FLEXGRID D2.2, https://flexgrid-project.eu/assets/deliverables/FLEXGRID_D2.2_final_31032020.pdf

[11] FLEXGRID D5.1, https://flexgrid-project.eu/assets/deliverables/FLEXGRID_D5.1_final_03122020.pdf

- upward reactive power (MVAr – euros/MVAr), and
- downward reactive power (MVAr – euros/MVAr).

Uncertainties pertaining to market competition and local grid consumption/production power are not considered. We perform a deterministic analysis, allowing us to focus on studying the interactions between the individual markets, and how the ESP can manage its BSU portfolio to increase its profitability by participating in the four markets in a co-optimized manner. A stochastic optimization technique can be transparently implemented in the proposed model to tackle the afore-mentioned sources of uncertainty. In this case, however, an extensive computational burden would be added, so mathematical approaches such as decomposition techniques or robust optimization could offer interesting studies and promising solutions.

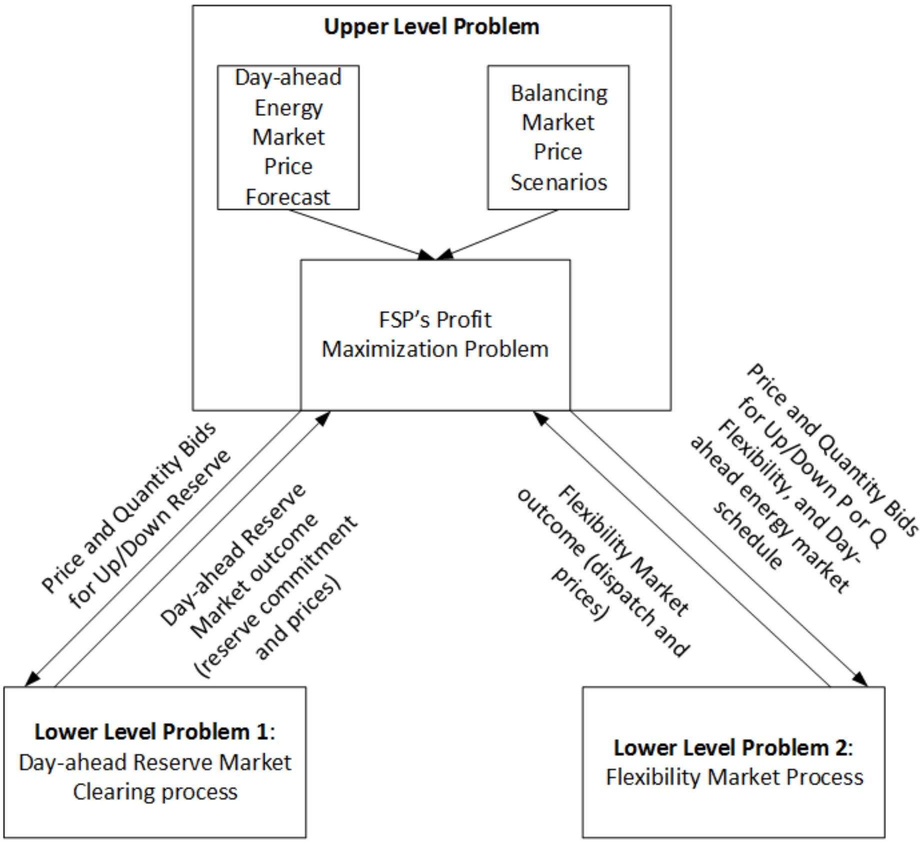

Figure 37: The proposed bi-level mathematical model

The bi-level model illustrated in the figure above is proposed to formulate the ESP's problem of determining the optimal bidding strategy and the charging/discharging schedule of the BSUs. In the upper level, the ESP decides on the BSUs' operating schedule and its bidding strategy, while taking as input the day-ahead energy market (DAM) prices and balancing market (BM) forecast prices and anticipating the impact of its decisions on the reserve and DLFM. The ESP's decisions include the energy traded in the day-ahead energy market, the price and quantity bids to the RM and DLFM and the power bought/sold in the BM.

In the lower-level, for given ESP's decisions, the TSO and the FMO clear the RM and the DLFM, respectively. In the RM and the DLFM clearing processes, the bids of the other market participants (i.e. rival ESPs) are treated as parameters. Moreover, the decisions of the DAM concerning the distribution-level demand and production are also treated as input parameters in the DLFM clearing process.

A detailed mathematical analysis is provided in chapter 5 of D4.2, so the interested reader can refer to this report for detailed technical information. In a nutshell, the following problems have been mathematically formulated:

- **Upper-level problem for ESP's profit maximization:** The objective function of the upper-level problem maximizes the ESP's overall profits from participating in all 4 four markets. This optimization is subject to several constraints such as battery charge/discharge related constraints, upward/downward reserve capacity provisioning to both TSO and DSO, quantity bid constraints, etc.
- **Lower-level problem 1 for clearing of the Reserve Market (RM):** The objective function minimizes the reserve capacity procurement cost based on the market participants' reserve prices and capacity offers. We assume that RM is cleared independently from the DAM.
- **Lower-level problem 2 for clearing of the DLFM:** The objective function minimizes the DN-level flexibility procurement cost. The FMO's objective is to ensure the necessary active and reactive flexibility at a minimum cost in order to address the possible contingencies (congestion and voltage issues). In other words, in case the DAM results violate the DN constraints, then the FMO will calculate the least-cost required flexibility dispatch and the selected DERs will have to re-adjust their DAM position based on the DLFM results, in order for the DSO to ensure a secure operation of its DN.

Finally, the non-linear bi-level problem described above can be recast into a Mathematical Program with Equilibrium Constraints (MPEC). To this end, we replace lower-level problems (1) and (2) with their respective Karush-Kuhn-Tucker (KKT) conditions. Note that these problems are continuous and linear, and therefore their KKT conditions are necessary and sufficient optimality conditions. The resulting single-level problem contains non-linear complementarity slackness conditions. which can be linearized using the Big-M approach. Moreover, in order to tackle the non-linearities in the objective function of the upper-level problem, we use the Strong Duality Theorem and the optimality conditions of the two lower-level problems as well as some algebraic operations. **For more technical details, the interested reader can follow up the respective material in chapter 5 of FLEXGRID D4.2 and our recently published paper in IEEE Transactions on Sustainable Energy[12].**

[12] K. Steriotis, K. Sepetanc, K. Smpoukis, N. Efthymiopoulos, P. Makris, E. Varvarigos, H. Pandzic, "Stacked Revenues Maximization of Distributed Battery Storage Units via Emerging Flexibility Markets", IEEE Transactions on Sustainable Energy, October 2021, https://ieeexplore.ieee.org/document/9557813.

5.5 Performance Evaluation Results

5.5.1 Simulation setup

This section studies the performance of our proposed mathematical model and algorithm using a modified IEEE 33-Bus test distribution system. The algorithm is implemented in MATLAB and in each iteration, the MILP problem is solved using Gurobi 9.0.2. All simulations were performed on a personal computer with Intel Core i7 4.00GHz and 32 GB RAM.

The single-line diagram of the IEEE 33-Bus test system is illustrated in the **Figure 38**. The total installed distributed generation (DG) nominal capacity is 39 MW and the total base load is 18.575 MW and 11.5 MVAr respectively. Detailed network, load and generation data of this modified system can be found in the respective FLEXGRID Github repository[13]. We considered two 2.5 MW x 1.6h BSUs, located at buses 24 (i.e. ES1) and 30 (i.e. ES2) in the distribution network (see **Figure 38**). Their discharging/charging efficiencies are set to $\eta_i^d = \eta_i^c$ =0.93, while the initial state of energy of the BSUs is assumed to be 87.5%. Thirteen competing ESPs are assumed to provide flexibility services to the DSO through their participation in the DLFM. These ESPs control assets that are located at buses 13, 14, 16, 17, 18, 22, 24, 25, 29, 30, 31, 32 and 33 and their active and reactive power bidding prices are set to 15€/MWh and 3€/MVAr, similar to a recently published work[14]. Data from Mavir, the Hungarian TSO, and the HUPX, the Hungarian Power Exchange, were used for the Day-Ahead Energy, Reserve and Balancing Markets. Regarding the Reserve Market, data from the Frequency Containment Reserve (FCR) Market clearing process were used. Balancing Market price scenarios were formed from historical data of the Mavir's Balancing Energy Market. An interested reader can find a complete list of input data in the FLEXGRID Github repository mentioned above. Finally, a daily (24h) time horizon is considered.

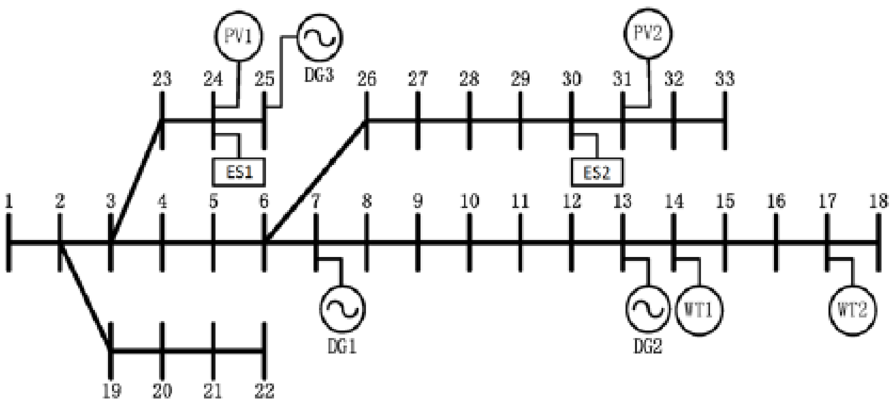

Figure 38: IEEE 33-node distribution system used for testing and performance evaluation purposes

[13] https://github.com/FlexGrid/Battery_Stacked_Revenues

[14] L. Bai, J. Wang, C. Wang, C. Chen, and F. Li, "Distribution Locational Marginal Pricing (DLMP) for Congestion Management and Voltage Support", IEEE Trans. Power Systems, vol. 33, no. 4, pp. 4061-4073, Jul. 2018.

5.5.2 Performance evaluation results

In order to evaluate the proposed model, we examine and compare the following four cases:

- **Case 1:** The ESP provides (energy and reserve) services to the TSO only through its participation in the DAM and RM.
- **Case 2:** The ESP delivers flexibility services to the DSO through its participation in the DLFM. For its upward/downward P-flexibility provided to the DSO, the ESP will be paid or will pay the BM price.
- **Case 3:** The ESP participates in all four markets (DAM, RM, DLFM, and BM) in a sequential manner. More specifically, the ESP initially optimizes its BSU portfolio in order to maximize its profits from a certain market, without taking into consideration the markets that follow.
- **Case 4:** The ESP participates in all four markets adopting the proposed model that co-optimizes the ESP's participation (and thus its expected total profits) in all four markets.

In Case 1, the ESP makes profits from providing energy and frequency regulation services to the TSO through its participation in the day-ahead energy and the reserve market, respectively. The table below illustrates the scheduling and bidding decisions of the ESP, along with the DAM and RM prices. In this case, the ESP's main target is to guarantee that the BSUs will have the maximum capacity available to offer in the RM, since this market brings the highest profits. Hence, the ESP trades energy in the DAM mainly to gain more profit opportunities, but also to pre-charge energy in order to use it for the RM that follows. For example, the ESP sells (i.e., battery's discharge) total power of 2.86 MW in t = 1, when the energy price is higher (i.e., 36.09 euros/MW) as compared to the following hours. Moreover, this enables the ESP to offer higher downward regulation reserve capacity (i.e., 4.38 MW in t = 1). The ESP seldom performs energy arbitrage between the low-cost hours (e.g., t = 4 and t = 5) and high-cost hours (e.g., t = 8 and t = 9). In discharge hours, the ESP offers higher downward reserve capacity, while the BSUs' charging process (e.g., t = 4, t = 5, t = 17, t = 22-24) enables it to offer higher upward reserve capacity. However, in most hours, the ESP keeps its BSUs in idle mode (e.g., t = 2-3, t = 6-7, t = 10-16, t = 18-19 and t=21). The ESP's main objective is to offer high combined reserve capacity at all times (note that the upward and downward reserve prices are equal with the exception of t = 24, in which upward reserve price is 12.09 and downward reserve price is 12.73 euros/MW), while in parallel take advantage of the most significant energy price fluctuations over time in the DAM. Conclusively, the ESP gains 26.25 euros from its participation in the DAM, and 2,417.90 € from providing ancillary services to the TSO, resulting in a total profit of 2,444.20 €.

Table 6: ESP's scheduling and bidding decisions and market prices in Case 1

Hour	dis_t/ch_t (MW)	$r_t^{s,up}, r_t^{s,dn}$	$c_t^{s,up}, c_t^{s,dn}$ (€/MW)	λ_t^e (€/MW)	$\lambda_t^{up}, \lambda_t^{dn}$ (€/MW)
1	2.86	2.15,4.38	12.73, 12.73	36.09	12.73,12.73
2	-	3.65,4.38	12.73, 12.73	34.69	12.73,12.73
3	-	3.65,4.38	12.73, 12.73	35.08	12.73,12.73
4	-0.27	3.89,4.10	12.73, 12.73	34.57	12.73,12.73
5	-1.28	5,2.82	12.73, 12.73	34.75	12.73,12.73
6	-	5,2.82	12.73, 12.73	39.9	12.73,12.73
7	-	5,2.82	12.73, 12.73	49.8	12.73,12.73
8	1.55	3.45,4.61	12.73, 12.73	57.75	12.73,12.73
9	0.33	3.12,5	12.73, 12.73	58.6	12.73,12.73
10	-	3.12,5	12.73, 12.73	52.2	12.73,12.73
11	-	3.12,5	12.73, 12.73	48.81	12.73,12.73
12	-	3.12,5	12.73, 12.73	45.66	12.73,12.73
13	-	3.12,5	12.73, 12.73	45.46	12.73,12.73
14	-	3.12,5	12.73, 12.73	42.57	12.73,12.73
15	-	3.12,5	12.73, 12.73	41.92	12.73,12.73
16	-	3.12,5	12.73, 12.73	41.39	12.73,12.73
17	-2.18	5,2.82	12.73, 12.73	42.05	12.73,12.73
18	-	5,2.82	12.73, 12.73	46.02	12.73,12.73
19	-	5,2.82	12.73, 12.73	47.07	12.73,12.73
20	1.88	3.12,5	12.73, 12.73	62.41	12.73,12.73
21	-	3.12,5	12.73, 12.73	64.3	12.73,12.73
22	-0.96	3.95,4.04	12.73, 12.73	48.12	12.73,12.73
23	-0.10	4.03,3.94	12.73, 12.73	42.5	12.73,12.73
24	-2.86	6.51,1.08	12.09, 12.73	37.5	12.09,12.73

*A negative/positive value corresponds to the BSUs' charging/discharging mode

**$dis_t = \sum_{i \in S} dis_{i,t}$, $ch_t = \sum_{i \in S} ch_{i,t}$, $r_t^{s,up} = \sum_{i \in S} r_{i,t}^{s,up}$, $r_t^{s,dn} = \sum_{i \in S} r_{i,t}^{s,dn}$

In Case 2, the ESP provides flexibility (upward or downward, P- or Q-flexibility services) to the DSO. For the BSUs' active power activations decided in the DLFM, the ESP will also have to pay/be paid in the BM. The purpose of the existence and operation of a DLFM is to ensure a direct participation of the DERs in the wholesale (TSO) markets without putting at risk the distribution network operation. The energy market produces a dispatch that violates several distribution network constraints at multiple hours. The FMO runs the DLFM in order for the DSO to purchase flexibility services to stabilize its network. The DLFM clearing process results are presented in the table below. In this specific case study, taking into consideration the production of the DGs and the local demand decided in the DAM, the distribution network faces mostly the over-voltage and under-voltage issues, and thus, the DSO mostly requires Q-flexibility services. Hence, we see in the table below that the BSU at node 24 (see column 4) draws reactive power during most of the day, when the negative q-LMPs indicate the need for absorbing reactive power, while the BSU at node 30 (see column 5) offers reactive power in all hours (positive q-LMPs). The ESP chooses only a few hours during the day to offer upward or downward p-flexibility (active power) services and using only the BSU at node 24 (see column 2). More specifically, the BSU at node 24 draws active power at hours t = 11 and t = 15, when the absolute value of the negative p-LMP is high and, in parallel, the BM expected price is relatively low. On the other hand, the ESP chooses to discharge power at hours t = 7, t = 8 and t = 22 with zero p-LMP, since the BM prices are high enough. Overall, the ESP gains a total of 674.04 euros (571.81 euros from the DLFM and 102.23 euros from the BM).

Table 7: The DLFM clearing results in Case 2

Hour	$p^{s,up}_{1,t}/p^{s,dn}_{1,t}$ (MW)	$p^{s,up}_{2,t}/p^{s,dn}_{2,t}$ (MW)	$q^{s,up}_{1,t}/q^{s,dn}_{1,t}$ (MVAr)	$q^{s,up}_{2,t}/q^{s,dn}_{2,t}$ (MVAr)	$\lambda^{p}_{24,t}, \lambda^{p}_{30,t}$ (€/MW)	$\lambda^{q}_{24,t}, \lambda^{q}_{30,t}$ (€/MVAr)	$\sum_{\omega\in\Omega} \xi_\omega \cdot \lambda^{b}_{t,\omega}$ (€/MW)
1	0	0	-2.18	1.70	-10.27,2.98	-6.97,3	18.59
2	0	0	-2.31	1.57	-10.27,2.98	-6.97,3	21.96
3	0	0	-2.50	1.37	-10.27,2.98	-6.97,3	24.10
4	0	0	-2.50	1.19	-10.27,2.98	-6.97,3	25.52
5	0	0	-2.50	1.28	-10.27,2.98	-6.97,3	28.33
6	0	0	-1.93	1.96	-10.27,2.98	-6.97,3	33.14
7	0.70	0	-2.21	0.39	0,11.43	-0.05,8.47	61.73
8	0.69	0	-2.22	1.33	0,12.46	-0.25,8.87	25.98
9	0	0	-2.40	1.98	-9.59,13.74	-6.88,10.34	21.63
10	0	0	-2.50	1.47	-9.59,13.74	-6.88,10.34	38.24
11	-1.63	0	-1.83	0.89	-9.54,15	-6.87,11.24	12.76
12	0	0	-1.91	2.5	-15,3.55	-10.61,3	29.81
13	0	0	-2.5	2.5	-15,3.01	-10.40,3	39.82
14	0	0	-2.34	2.5	-15,3.01	-10.40,3	41.31
15	-0.52	0	-2.29	2.5	-9.94,3.44	-6.93,3	18.71
16	0	0	-2.5	2.5	-9.97,3.41	-6.93,3	41.56
17	0	0	-2.5	1.12	-9.59,13.74	-6.88,10.34	36.79
18	0	0	-0.91	2.45	-9.64,12.02	-6.89,9.12	24.53
19	0	0	1.65	2.19	1.83,15	0.93,10.54	21.85
20	0	0	2.28	2.5	1.52,12.55	0.78,8.83	32.62
21	0	0	0.88	2.5	1.51,12.53	0.77,8.82	36.68
22	1.87	0	-1.52	2.5	0.26,12.04	0,8.69	83.26
23	-0.73	0	-2.2	1.75	0,8.55	0,6.41	54.68
24	-0.89	0	0	2.5	-10.27,2.98	-6.97,3	50.47

*A negative/positive value corresponds to downward/upward flexibility services

In Case 3, the ESP initially decides on its energy trading in the DAM ignoring the next steps (i.e. participation in RM, DLFM and BM). Then, given the BSUs' power schedule, the ESP offers reserve capacity in the RM without considering its strategy in the subsequent markets. Finally, the ESP offers its remaining power capacity to the DSO in DLFM, disregarding the forecast BM prices, at which the ESP eventually will pay/be paid its DLFM active power dispatch. The table below illustrates the final BSUs' active/reactive power schedules and reserve capacity commitments. At first, the ESP performs energy arbitrage to maximize its profit from the DAM and results in 217.67 euros. This, however, hampers the BSUs' ability to offer regulation services through the RM. Comparing the RM prices from the respective tables in Case 1 and Case 3, we see that not co-optimizing the bidding strategies for energy and reserve leads to a reduction in the upward reserve prices during hours t = 4 and t = 16 and in the downward reserve prices during hours t = 9 and t = 21 by 5%. The lowered prices, along with the diminished available capacity to offer to the RM, reduce to a RM profit for the FSP of 1,699.70 euros, which is 30% lower than the profit that the ESP gains in the RM in Case 1 (i.e. 2,417.90 euros). On the other hand, the ESP's previous scheduling and bidding decisions leave the BSUs with neither the upward nor the downward active power capacity to offer to the DSO. Thus, the BSUs provide only q-flexibility in the DLFM, which is constrained by the maximum apparent power of the converter. Studying the DLFM q-LMPs in Cases 2 and 3 from the respective tables, we notice that the ESP, through its bidding policy, manages to increase by absolute value the DLFM prices at nodes 24 and 30 in most hours. However, the inability to provide p-flexibility services leaves the ESP earning 498 euros, which is 13% lower than the ESP's profits from DLFM in Case 2 (i.e. 571.81 euros). Ultimately, the myopic behavior of the ESP, which participates in each market disregarding the profit opportunities that follow, results in its total profit of 2,415.70 euros, which is 1.17% lower than in Case 1 (i.e. 2,444.20 euros), despite the fact that the ESP participates in all four markets. One advantage of sequential market participation (i.e. Case 3) is that the ESP is not exposed to the balancing market's uncertainties. In the specific case study, the BM profits are only 0.33 euros, which may be a good option for an ESP that wants to follow a conservative market participation policy.

Table 8: The BSUs' power and reserve schedules in Case 3

Hour	dis_t/ch_t (MW)	$r_t^{s,up}, r_t^{s,dn}$ (MW)	$p_{1,t}^{s,up}/p_{1,t}^{s,dn}$ (MW)	$p_{2,t}^{s,up}/p_{2,t}^{s,dn}$ (MW)	$q_{1,t}^{s,up}/q_{1,t}^{s,dn}$ (MVAr)	$q_{2,t}^{s,up}/q_{2,t}^{s,dn}$ (MVAr)	$\lambda_t^{up}, \lambda_t^{dn}$ (€/MW)	$\lambda_{24,t}^{p}, \lambda_{30,t}^{p}$ (€/MW)	$\lambda_{24,t}^{q}, \lambda_{30,t}^{q}$ (€/MVAr)
1	0	5,1.08	0	0	-1.99	2.06	12.73,12.73	-10.27,2.98	-6.97,3
2	0	5,1.08	0	0	-2.11	1.93	12.73,12.73	-10.27,2.98	-6.97,3
3	0	5,1.08	0	0	-2.37	1.71	12.73,12.73	-10.27,2.98	-6.97,3
4	-1.08	6.08,0	0	0	-1.77	2.28	12.09,12.73	-10.27,2.98	-6.97,3
5	0	5,0	0	0	-2.49	1.63	12.73,12.73	-10.27,2.98	-6.97,3
6	0	5,0	0	0	-1.74	2.32	12.73,12.73	-10.27,2.98	-6.97,3
7	0	5,0	0	0	-0.98	2.50	12.73,12.73	-10.27,2.98	-6.97,3
8	2.44	2.56,2.82	0	0	-1.99	1.99	12.73,12.73	-10.01,3.36	-6.94,3
9	5	0,8.6	0	0	0	0	12.73,12.09	-9.92,3.25	-6.93,3
10	0	0,5	0	0	-2.5	1.81	12.73,12.73	-9.54,15	-6.87,11.24
11	0	0,5	0	0	-2.5	1.14	12.73,12.73	-9.17,15	-6.82,10.85
12	0	0,5	0	0	-1.75	2.5	12.73,12.73	-15,3.54	-10.62,3
13	0	0,5	0	0	-2.4	2.5	12.73,12.73	-15,3.54	-10.62,3
14	0	0,5	0	0	-2.12	2.5	12.73,12.73	-15,3.54	-10.62,3
15	-3.60	3.12,1.40	0	0	-1.69	1.69	12.73,12.73	-9.26,15	-6.83,10.94
16	-5	7.44,0	0	0	0	0	12.09,12.73	-9.54,15	-6.87,11.24
17	0	5,0	0	0	-2.5	1.50	12.73,12.73	-9.54,15	-6.87,11.24
18	0	5,0	0	0	-0.72	2.37	12.73,12.73	-9.17,15	-6.82,10.85
19	0	5,0	0	0	1.88	2.50	12.73,12.73	1.83,15	0.93,10.54
20	2.44	2.56,2.82	0	0	0.61	1.99	12.73,12.73	1.55,12.57	0.79,8.83
21	5	0,8.60	0	0	0	0	12.73,12.09	-9.65,12	-6.89,9.11
22	0	0,5	0	0	1.40	2.5	12.73,12.73	1.02,12.07	0.52,8.67
23	-2.53	2.19,2.47	0	0	1.98	1.98	12.73,12.73	0.61,15	0.31,11
24	-5	6.51,0	0	0	0	0	12.73,12.73	0.61,15	0.31,11

*A negative/positive value corresponds to the BSUs' charging/discharging mode or downward/upward flexibility services

**$dis_t = \sum_{i\in S} dis_{i,t}$, $ch_t = \sum_{i\in S} ch_{i,t}$, $r_t^{s,up} = \sum_{i\in S} r_{i,t}^{s,up}$, $r_t^{s,dn} = \sum_{i\in S} r_{i,t}^{s,dn}$

Implementation of the proposed FLEXGRID bidding strategy, which co-optimizes the stacked revenues of the ESP coming from all four markets under study (i.e. Case 4), produces the results presented in the table below. In this Case, the ESP attempts to take advantage of all business opportunities and it achieves DAM profits far higher (i.e 974.09 euros) than in Cases 1 or 3. Note that the DAM dispatch does not determine the BSUs' state-of-charge alone, but it is only one of the two components of the final charging/ discharging schedule (the other one is the DLFM active power dispatch). Thus, the ESP can perform arbitrage between the DAM and the DLFM (discharge in DAM and charge in DLFM and vice versa), in contrast with Cases 1, 2 and 3 where the ESP does not have this opportunity. Therefore, the ESP chooses to trade energy in the DAM much more frequently than in the previous Cases. The ESP's decision on the charging/discharging DAM schedule of the two BSUs does not consider only the DAM prices, but also the profit opportunities in the RM, the nodal DLFM prices (and therefore the location of each BSU in the distribution network) as well as the expected BM prices. More specifically, the ESP, expecting the p-LMPs at node 24 to be negative (DSO's signal that it needs downward p-flexibility in this area) during most of the day (t = 1-18, 24), uses the BSU at this node at maximum discharge power (2.5 MW) in hours t = 1-4, 8-13, 15 and 18. In this way, the ESP creates profit opportunities in the RM by maximizing its available downward reserve capacity. However, in order for the ESP to be able to sell energy and downward regulation in the DAM and the RM respectively, the ESP has to provide downward p-flexibility to the DSO, even if it means that the ESP will have to pay for it, since the expected BM prices are higher in absolute value than the DSO's reward per unit. Hence, the ESP commits the maximum downward reserve capacity to the RM that the state-of-charge constraints of the BSU allow and the rest of the available downward power capacity is sold in the DLFM (see the two figures below).

Table 9: The BSUs' power and reserve schedules in Case 4

Hour	$dis_{1,t}/ch_{1,t}$, $dis_{2,t}/ch_{2,t}$ (MW)	$r_{1,t}^{s,up}, r_{2,t}^{s,up}$ (MW)	$r_{1,t}^{s,dn}, r_{2,t}^{s,dn}$ (MW)	$p_{1,t}^{s,up}/p_{1,t}^{s,dn}$ (MW)	$p_{2,t}^{s,up}/p_{2,t}^{s,dn}$ (MW)	$q_{1,t}^{s,up}/q_{1,t}^{s,dn}$ (MVAr)	$q_{2,t}^{s,up}/q_{2,t}^{s,dn}$ (MVAr)	$\lambda_t^{up}, \lambda_t^{dn}$ (€/MW)	$\lambda_{24,t}^{p}, \lambda_{30,t}^{p}$ (€/MW)	$\lambda_{24,t}^{q}, \lambda_{30,t}^{q}$ (€/MVAr)
1	2.5,2.5	0,0	1.61,2.5	-1.81	-0.93	-2.22	1.82	12.73,12.73	-10.36,0	-6.99,0.86
2	2.5,0	0,1.56	2.11,2.5	-2.40	0	-2.46	1.57	12.73,12.73	-10.27,2.98	-6.97,3
3	2.5,0	0,1.56	2.22,2.5	-2.78	0	-2.16	1.38	12.73,12.73	-10.27,2.98	-6.97,3
4	2.5,-0,.46	0,1.96	2.25,2.04	-2.75	0	-2.40	1.84	12.73,12.73	-10.27,2.98	-6.97,3
5	0.85,-0.67	1.65,2.54	2.39,1.37	-0.96	0	-2.45	2.22	12.73,12.73	-10.27,2.98	-6.97,3
6	0.7,-0.29	1.80,2.79	2.22,1.07	-0.98	0	-1.49	2.38	12.73,12.73	-10.27,2.98	-6.97,3
7	1.77,0	0.03,1.27	4.27,2.5	0	1.23	-1.77	1.03	12.73,12.09	-10.27,2.98	-6.97,3
8	2.5,0	0,1.56	2.14,2.5	-2.86	0	-0.66	1.47	12.73,12.73	-9.68,11.99	-6.89,9.12
9	2.5,0	0,1.56	1.51,2.5	-3.49	0	-0.95	2.02	12.73,12.73	-9.59,13.74	-6.88,10.34
10	2.5,-0.21	0,1.74	2.71,2.29	-2.29	0	-2.41	1.76	12.73,12.73	-9.59,13.74	-6.88,10.34
11	2.5,-0.88	0,2.5	0,1.41	-5	0	0	2.14	12.73,12.73	-9.26,15	-6.83,10.94
12	2.5,0.71	0,1.79	2.77,2.23	-2.23	0	-2.39	2.21	12.73,12.73	-15,3.14	-10.50,3
13	2.5,0.16	0,1.63	2.52,2.41	-2.48	0	-2.49	2.43	12.73,12.73	-15,3.01	-10.40,3
14	1.94,0	0.56,1.63	2.59,2.41	-1.85	0	-2.46	2.5	12.73,12.73	-15,3.01	-10.40,3
15	2.5,0	0,1.63	0.73,2.41	-4.27	0	-1.77	2.5	12.73,12.73	-9.94,3.44	-6.93,3
16	0.86,0	1.64,1.56	2.41,2.5	-0.86	0.07	-2.5	2.47	12.73,12.73	-9.97,3.41	-6.93,3
17	0.60,-0.80	1.90,2.25	2.11,1.7	-1.00	0	-2.34	2.17	12.73,12.73	-9.54,15	-6.87,11.24
18	2.5,-0.14	0,2.37	1.86,1.56	-3.14	0	0	2.16	12.73,12.73	-9.54,15	-6.87,11.24
19	-0.45,-0.16	2.50,2.50	1.41,1.41	0	0	2.31	2.43	12.73,12.73	1.83,15	0.93,10.54
20	0,0	2.50,2.50	1.41,1.41	0	0	2.28	2.5	12.73,12.73	1.52,12.55	0.78,8.83
21	-0.34,-0.39	2.80,2.84	1.07,1.02	0	0	2.36	2.34	12.09,12.73	1.30,15	0.66,10.75
22	-2.5,-2.5	0.61,1.73	0,0	4.35	3.27	-1.58	1.69	12.73,12.73	0.26,12.04	0,8.69
23	-2.30,-2.5	2.60,2.34	0.20,0	0	1.55	0.48	2.11	12.73,12.73	0.60,15	0.31,11
24	-0.76,-2.5	3.26,3.26	0.54,0	0	1.24	-0.07	1.98	12.09,12.73	-10.03,11.02	-6.94,8.76

*A negative/positive value corresponds to the BSUs' charging/discharging mode or downward/upward flexibility services

In hours 5–7, 14, 16 and 17, the BSU at node 24 is decided to discharge power, but not at its full capacity. This produces available upward reserve and enables the ESP to also provide upward reserve capacity in the RM. This capacity is entirely sold in the RM, except in hour when state-of-charge constraints do not allow it (see figure below). In hours 20–23, the p-LMPs are positive, indicating that the DSO requires upward p-flexibility. However, a constraint of upper-level problem dictates the BSU at node 24 to charge power in order to restore the state-of-charge at the end of the day. Nevertheless, in hour 22, the BM price is expected to reach its peak (83.26 euros), and thus the ESP provides the DSO with 4.35 MW of upward p-flexibility, even if the DLFM price is quite low at this time.

At node 30, i.e. the location of the second ESP's BSU, the DSO requires only upward p- and q-flexibility services throughout the day (except for the first hour, when $\lambda_{30,1}^{p}$ = 0). In order for a BSU to be able to provide upward p-flexibility services, it should buy power in DAM. Thus, the main criterion for the ESP to decide whether the BSU will sell active power in the DLFM is the comparison between the energy price (at which the ESP will have to pay the charging power) and the sum of the pLMP at node 30 and the expected BM price (at which the ESP will be paid for the upward p-flexibility service). Therefore, the BSU at node 30 provides upward p-flexibility services to the DSO in hours 7, 16, 22, 23 and 24, when this is financially advantageous (see Figure 41). During the rest of the day, we see in the table below that the BSU chooses to trade power in the DAM, with the objective to have the highest possible available upward and downward reserve capacity. Hence, as shown in Figure 39, the BSU offers upward reserve capacity throughout the day and downward reserve capacity from the beginning of the day until hour 21. In the last 3 hours, the high profit opportunities in DLFM and BM leads the ESP to leave no space for downward reserve capability.

Finally, throughout the day, the ESP makes profit by also providing voltage support services to the DSO, by absorbing (in hours when the q-LMP is negative) or supplying (in hours when the q-LMP is positive) reactive power to the grid. The capability of the BSUs to trade reactive power depends on their active power schedule and the apparent power rating of the converters. For example, in hours 12, 13 and 14, when the absolute values of the q-LMPs at node 24 are the highest throughout the day, the aggregate active power schedule of the BSU located at this node is close to zero. Therefore, the BSU can absorb reactive power at a rate very close to the maximum and increase its profits. On the contrary, in hour 11 the aggregate active power dispatch of the same BSU leaves no room for reactive power services, since it reaches the maximum apparent power potential of the BSU. At node 30, the BSU supplies reactive power the local grid at all times, as the positive q-LMPs dictate.

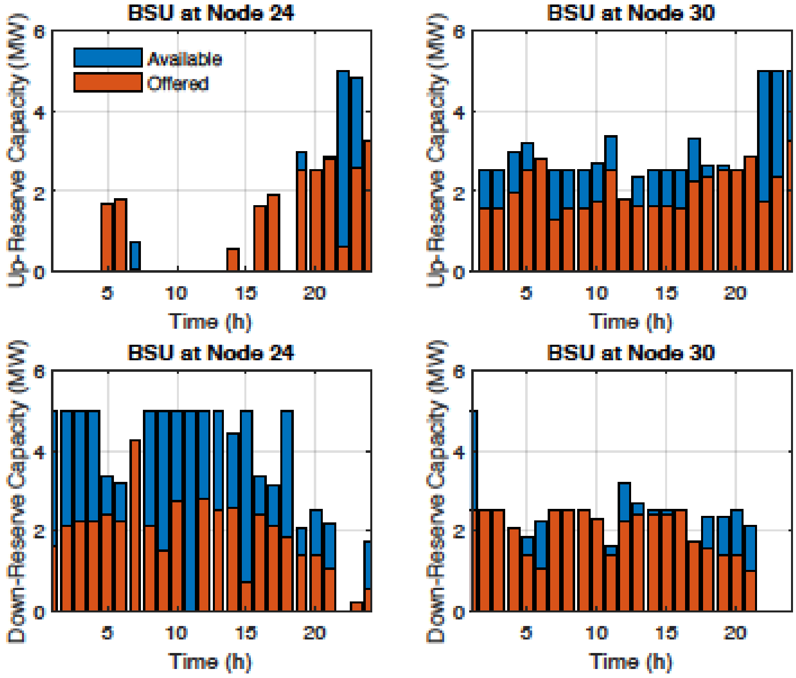

Figure 39: BSUs' available and offered reserve capacity to the RM

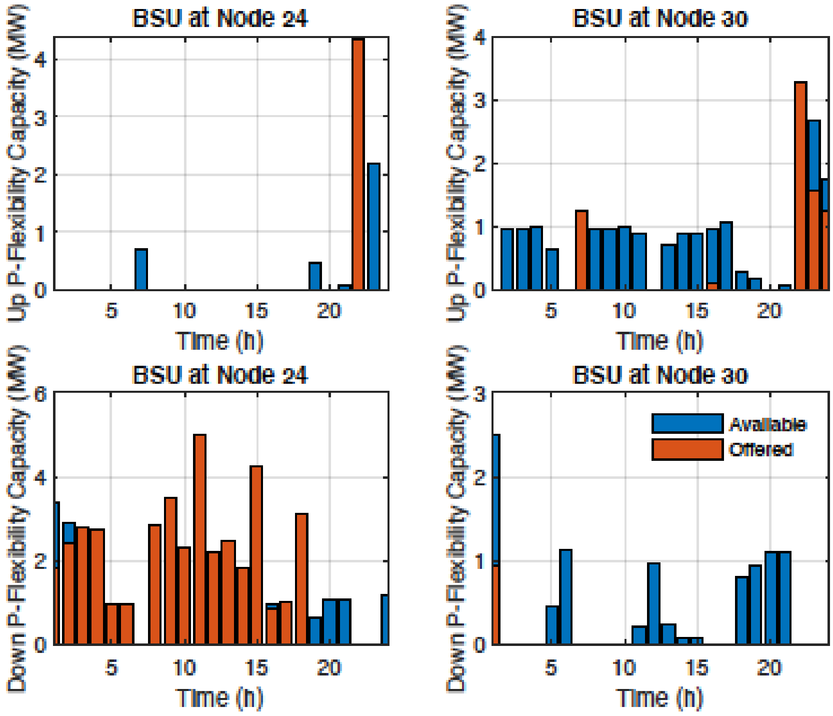

Figure 40: BSUs' available and offered active power capacity to the DLFM

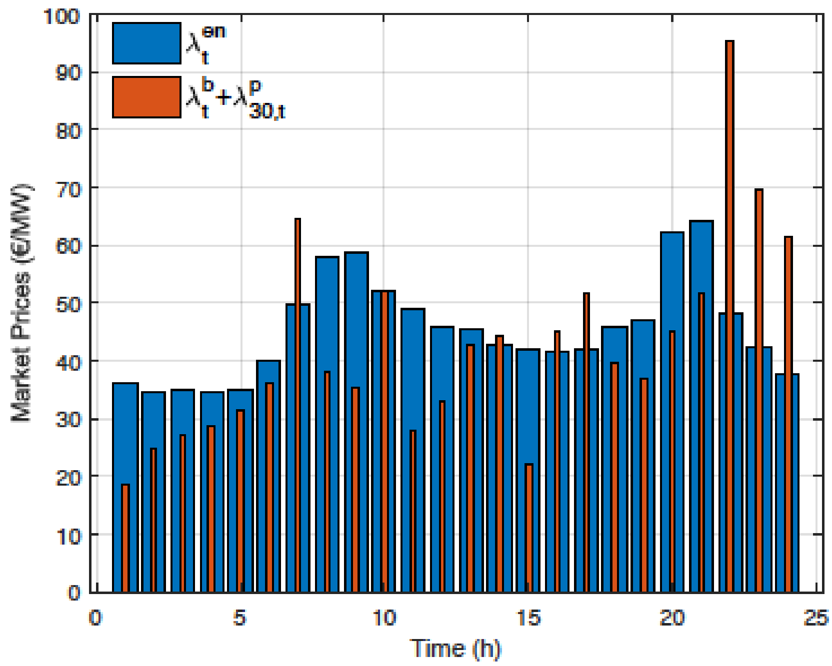

Figure 41: Comparison between the DAM prices and the sum of the BM and the active power DLFM prices

Overall, the summary in Table 10 indicates that the RM profits in Case 4 are lower than in Case 1, but higher than in Case 3. In Case 1, the ESP, co-optimizing the energy and reserve services to the TSO, tries to maximize its storage capacity that is available to be offered to the TSO for regulation purposes, using the energy market. In Case 4 though, the ESP chooses not to offer its entire available capacity in the RM, since the DLFM and the BM, which chronologically follow, provide additional revenue streams. Even so, being much more active in the DAM comparing to Case 3, the ESP has higher reserve potential in Case 4 and thus derives 14.7% higher RM revenues (i.e. 1,950.60 euros). The ESP's decisions bring it profits of 1,101.70 euros from the DLFM, which surpass by far the ESP's profits from the local grid services in Cases 2 and 3 (higher by 92.67% and 121.22%, respectively). However, the BSUs' p-flexibility services provision to the DSO, which modify the agreed energy schedule in the DAM, lead the ESP to pay in the BM 210.94 euros, in contrast with the Case 2, in which the ESP earns 102.23 euros and Case 3, in which the ESP has negligible BM revenues. In Table 9, the aggregate ESP's profits in all four Cases are presented.

Our proposed strategy achieves a total gain of 3,815.45 euros, which is *super-linear*, i.e. the revenues from jointly optimizing the BSUs' services to both the TSO and the DSO are larger than the sum of performing the individual applications (Case 1 and Case 2). In fact, the ESP earns 22.36% higher revenues in Case 4, than in Cases 1 and 2 combined. Moreover, the proposed FLEXGRID model (Case 4) accomplishes 57.95% higher revenues than the 'myopic' strategy of Case 3.

Table 10: Summary of ESP's revenues per market and case under investigation

	DAM Revenues (€)	RM Revenues (€)	DLFM revenues (€)	BM Revenues (€)	Total ESP's revenues (€)
Case 1	26.25	2,417.90	-	-	2,444.20
Case 2	-	-	571.81	102.23	674.04
Case 3	217.67	1,699.70	498	0.33	2415.70
Case 4	974.09	1,950.60	1,101.70	-210.94	3,815.45

We now further study several sensitivity parameters of the proposed decision-making procedure (cf. case 4 above) and the profitability of the ESP to some externalities, such as the location of the BSUs and the competing ESPs' offers.

5.5.2.1 Impact of the Location of BSUs

In this subsection, we demonstrate how the siting of the BSUs (i.e. the nodes in the distribution network) affects the profitability of the ESP. For this purpose, we consider three potential scenarios for the BSUs' locations, namely: i) nodes 3 and 19, ii) nodes 18 and 33 and iii) nodes 25 and 31. The ESP's individual market revenues for each location scenario are illustrated in the figure below. In the first scenario, the BSUs are located close to the root of the distribution grid, where the demand for flexibility, and correspondingly the DLFM prices are low.

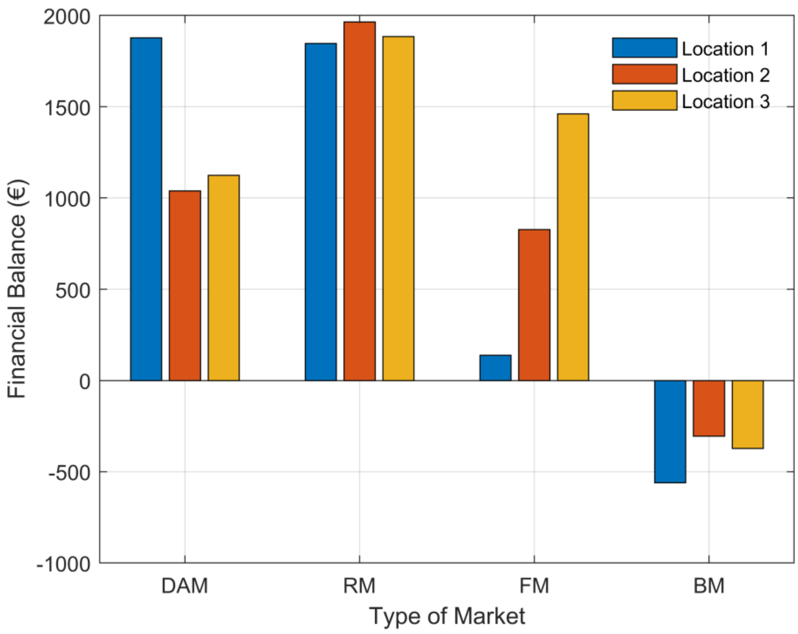

Figure 42: Breakdown of the ESP's market revenues for each BSU location under investigation

In this case, the ESP exploits the DSO's FlexRequest for downward P-Flexibility, so as to perform market arbitrage and sell energy in the DAM. Thus, we observe that the DAM profits in this scenario are higher than in any other market. The second highest source of revenues for the ESP is the RM, while in the DLFM the ESP is paid for its Flexibility services at a relatively low price. In the BM, the ESP pays for its downward p-Flexibility services. In the second scenario, the BSUs are located at the edges of the distribution network. At first, the BSU at node 18 mainly offers downward p-flexibility services in the DLFM, which gives it the opportunity to sell power in the DAM. The BSU at node 33 charges power in the DAM occasionally, so as to offer upward p- and mostly q-flexibility as a voltage support service to the DSO. Both BSUs take advantage of their available upward and downward reserve capacity, in order to increase their profitability via their participation in the RM. Finally, in the third scenario, the BSUs are placed at nodes 25 and 31, where the DSO's need for flexibility is rather high, rendering the DLFM much more profitable for the ESP than in the other two scenarios. The BSU at node 25, since the DG3 production (see IEEE. 33-node test system in figure above) mainly requires the provision of downward p-flexibility, is eligible to sell energy in the DAM during most of the day. On the other hand, the under-voltage issues at node 31 force the DSO to demand upward Q- and P-Flexibility services, which leads this BSU to strategically lose money in the DAM in order to offer remunerative flexibility services to the DSO. Overall, the total revenues for the ESP are higher for location 3 (4,097€), followed by location 2 (3,525.5€) and location 1 (3,302.7€) profits.

5.5.2.2 Impact of competing ESPs' price offers

Previously, we assumed that price offers of the competing ESPs are 15€/MW for p-Flexibility and 3€/MVAr for q-Flexibility services. Now, we study the effect that the magnitude of these offers has on the results that our bidding strategy produces. To this end, we examine three scenarios of the price offers presented in the table below. The individual market ESP's revenues for each scenario are presented in the figure below. The DLFM profits increase when increasing the competing ESP's offers since the DLFM prices rise. On the other hand, the DAM profits plummet in Scenario 2 and 3 comparing to Scenario 1. This is explained by the fact that higher DLFM prices prompt the ESP to provide upward P-Flexibility services to the DSO at node 30. To do that, the BSU at this node has to charge higher amounts of power in the DAM and ultimately downscale the DAM revenues. Additionally, in Scenario 2, the ESP, in contrast with Scenario 1, makes a small profit in the BM, which is even higher in Scenario 3. This is justified since the increase of the DLFM prices (and their comparison to the DAM prices) makes it profitable for the ESP to provide upward P-Flexibility services, which are compensated in both the DLFM and the BM. Conclusively, the ESP in Scenarios 2 and 3 gains 66.57% and 146.56% higher profits than in Scenario 1 (i.e. 6355.5€ and 9407.6€ as compared to 3815.5€).

Table 11: Scenarios of competing ESPs' price offers

	$c_{i,t}^{s,P,up}/c_{i,t}^{s,P,dn}$ (€/MW)	$c_{i,t}^{s,Q,up}/c_{i,t}^{s,Q,dn}$ (€/MVAr)
Scenario 1	15	3
Scenario 2	45	9
Scenario 3	75	15

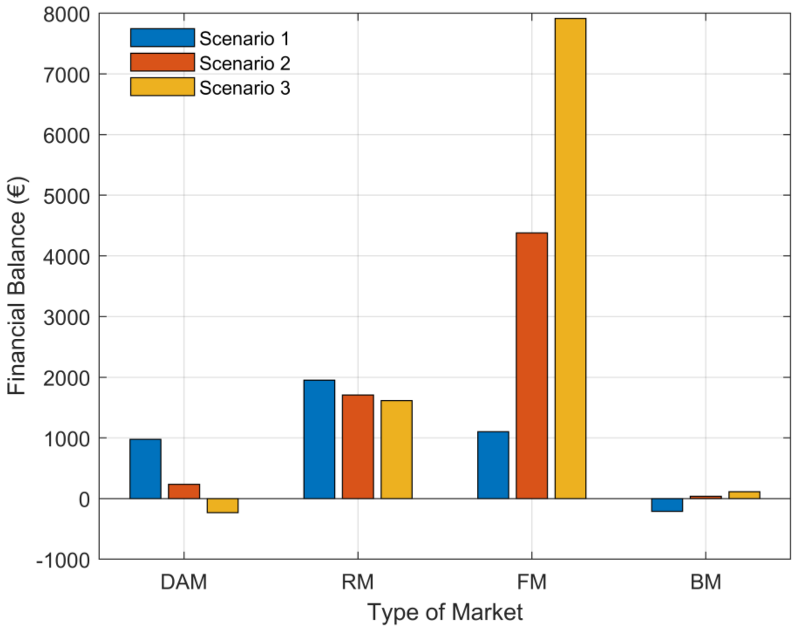

Figure 43: ESP's individual market revenues in each price offer scenario

5.5.2.3 Impact of the size of BSUs

In this subsection, we demonstrate how the size of the BSUs affects the profitability of the ESP. Hence, we consider 3 different BSUs' sizes: a) 1.25MW/2MWh, b) 2.5MW/4MWh, and c) 3.75MW/6MWh. The individual market ESP's revenues for each scenario are presented in the figure below, which illustrates, as expected, that as the size of the BSUs increases, the ESP's market profitability also rises. An ESP with installed BSUs of 2.5MW/4MWh (Scenario 2) makes revenue of 3815.5€, while with half installed BSUs power (Scenario 1) gains 1986.3€ (47.94% less than Scenario 1). In Scenario 3, with 1.5 times more BSUs power than in Scenario 2, the ESP earns 5555.6€, i.e. 45.61% higher total revenues.

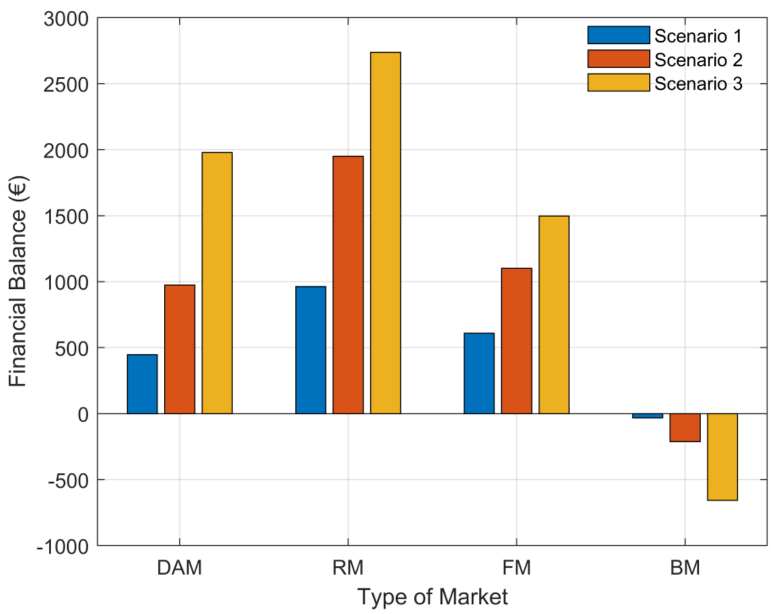

Figure 44: Breakdown of the ESP's market revenues for various BSUs sizes

5.6 Lessons learnt and roadmap towards Horizon Europe 2021-2027

In FLEXGRID UCS 2.3, we considered a novel market architecture (i.e. Reactive DLFM) that introduces a distribution level flexibility market (DLFM) operating in the intra-day timeframe, between the day-ahead energy and the near-real-time balancing markets. In this context, we formulated a bi-level model for an ESP that owns distributed BSUs to optimally calculate its market participation strategy. Performance evaluation results demonstrate that **our model achieves super-linear gains: the ESP obtains significantly higher revenues through the joint optimization of both the TSO and the DSO services than the sum of the individual profits from devoting the BSUs to one of the two applications.** Finally, a sensitivity analysis was conducted to showcase the impact of some externalities on the results (i.e. siting and sizing of BSUs as well as competing ESP's offers). The proposed model can be of use to flexibility providers in the modern electricity market structure that accommodates a distribution-level flexibility market. Such market is expected in the democratized and DG-rich power systems. Furthermore, our work can provide useful insights to policy makers, regulators and market operators regarding the operation of the DLFM and the TSO-DSO interaction. As a future work, we find it worthwhile to take into account uncertainties in renewable generation, load and market competition, and study the impact of the associated risks on the ESP's profitability. Finally, our future research will be focused on the balancing stage, including the activation of reserves.

After communicating FLEXGRID UCS 2.3 scientific results to both academic and industrial communities, we have come up with a short list of lessons learned that could be further investigated in future R&I initiatives. The Table 12 summarizes research and business-related insights for each one of the lessons learned.

Table 12 - Lessons learnt for UCS 2.3

Lesson learnt	Research & Business insights
An ESP should be aware of the grid constraints in order to be able to get the best possible financial revenues and at the same time help the system operators in the most efficient way	Efficient data sharing between profit-based ESPs and the rather 'neutral' system operators is not a straight-forward business process, because the latter (and especially DSO) are not willing to disclose critical information regarding the operational process of the grid. More research is needed in order for the ESP to be able to easily, effectively and in near-real-time be informed about the network needs
ESP profitability highly depends on the energy market architecture, related grid specifications and regulatory rules	Need to further research on the impact that energy market architecture may have on ESP's profitability. The regulator should make sure that it does dis-incentivize new flexibility investments and even guarantee a minimum profit/RoI for the ESP (cf. with the need for economically sustainable investments).
Strategic ESP market participation may yield undesirable market manipulation	Market Operators need to devise novel market clearing mechanisms that dis-incentivize ESPs

phenomena especially in cases in which the ESP has significant market power in addressing a local network contingency	from manipulating the market at the expense of incurring additional energy costs for the system. On the other hand, the economic sustainability of flexibility procurement by ESPs should also be guaranteed.
Market price forecasting errors are expected to directly affect the ESP's revenues	Volatility of DLFM and balancing market prices is expected to be high, while day-ahead energy market and reserve market prices can be predicted with much less mean absolute percentile error. However, high volatility in market prices implies more potential revenues for the ESP. Thus, an advanced risk analysis is required in order to calculate the conditional value at risk (CVaR) and other related KPIs.
A deterministic analysis may not be able to deal with many types of uncertainties that may come up in the ESP's real-life business	Stochastic optimization techniques can be developed to deal with uncertainties pertaining to market competition, network needs, consumption/RES production curves, etc. However, a heavy computational burden will be introduced and thus advanced decomposition techniques will be needed in order for the ESP to be able to compute its optimal bidding strategy in near-real-time context.
The location and the size of ESP's flexibility assets directly affect its profitability.	Optimal flexibility planning (cf. UCS 2.2) and stacked revenues' maximization business processes should be closely inter-related.
Accurate FlexAsset modeling can significantly affect the ESP's stacked revenues. The problem is that current models produce too optimistic results that may have large negative impact on ESP's profits.	More accurate FlexAsset (i.e. battery storage system) modeling is needed that is much closer to real-life operation of these flexibility assets (cf. UCS 2.1 results).

6 Market-aware and network-aware bidding policies to optimally manage a virtual FlexAssets' portfolio of an ESP (UCS 2.4)

This chapter deals with the research problem of FLEXGRID UCS 2.4. In this deliverable, we elaborate on our ongoing research work that has been reported in chapter 6 of D4.2 (i.e. Month 18). In D4.2, we provided a thorough and extensive mathematical model and algorithmic solution together with intuitive performance evaluation results.

Summarizing our contribution so far, we considered an ESP that controls a virtual and heterogeneous flexibility assets' portfolio (i.e., set of Virtual Power Plants) throughout the transmission grid, and participates in an imperfect wholesale electricity market. The portfolio consists of heterogeneous flexibility assets, namely: i) loads that must be satisfied by all means, ii) distributed RES generation, iii) energy storage capacity and iv) shiftable loads. Complementarity modeling is proposed to derive both the optimal schedule of heterogeneous flexibility assets and strategic market decisions for ESP. In the proposed model, the distribution network constraints are taken into account in order for the ESP's quantity and price market bids to be network-aware and thus reliable. Hence, a Mathematical Problem with Equilibrium Constraints (MPEC) is formulated, which is transformed into an equivalent Mixed Integer Linear Programming (MILP) model. We have shown that the proposed methodology results in significantly larger profit for the ESP, even if it possesses a small portion of market's production and/or consumption capacity. Moreover, we have investigated the impact on the results of Renewable Generators (RGs), flexible loads and Energy Storage Systems' (ESSs) location and size. Finally, we have shown that if distribution network constraints are not considered, this results in infeasible and costly dispatch schedules.

Following up the above-mentioned results, our next research step was to apply the proposed mathematical model and algorithm for a MicroGrid Operator's (MGO) business case. The main difference is that we consider remote energy communities (or else energy islands), which experience weak grid connections. In this business case, it is generally more appropriate for the MGO to be able to guarantee self-adequacy and thus be able to operate in an islanded mode as much as possible. This is achieved via maximizing local RES usage and minimizing the cost of energy in the microgrid. Within M19-M26 period, we adapted the existing mathematical model and algorithm and derived interesting performance evaluation results that are reported in this chapter.

6.1 Introduction to the energy island business case

Energy islands and remote energy communities with weak grid connections can be the EU's "front-runner" use case towards the energy transition[15], as they can benefit from:

- low cost of RES (especially taking into consideration EU's energy transition strategy and ambition for worldwide RES leadership within the next decades) compared to the high energy production costs of conventional generators,
- deployment of local RES and storage systems, which can both enhance cost effectiveness and decarbonize the local energy system in the long term, and
- the exploitation of the close social bonds of the local community members that increase end users' engagement [16,17].

Recent EU regulations[18] that incentivize local investments in integrated energy systems, highlight that the need for optimal RES investments triggers investments in flexibility assets, too (e.g. Electric Vehicles - EVs, Battery Storage Systems - BSS, Demand Side Management - DSM, etc.). Therefore, their efficient siting, sizing and scheduling becomes an apparent problem to solve towards the effective utilization of local RES usage.

Moreover, the underlying network of a typical energy island/ remote energy community/ microgrid is vulnerable to severe instability issues, because:

- its interconnection point with higher voltage networks (i.e. main grid at the transmission network level) is 'weak', and
- its existing lines at the distribution network level are usually inadequate to accommodate the continuously increasing RES penetration, especially at the edges of the low-voltage distribution network[19].
- the peak load requirement is usually quite different in various seasons of the year (e.g. in EU islands, the peak load is much higher in the summer months due to increased population and respective energy demand needs)

Finally, when not operating in islanded mode, the MicroGrid Operator (MGO) purchases/sells energy from/to the main grid to cover/sell its excessive demand/supply. Hence, **network- and market-aware bidding is required to minimize energy cost and maximize end users' welfare**.

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[15] A. Nouicer and L. Meeus, "The EU Clean Energy Package (2019 ed.)", European University Institute, October 2019.

[16] L. Steg, R. Shwom, T. Dietz, "What Drives Energy Consumers?: Engaging People in a Sustainable Energy Transition," *IEEE Power and Energy Magazine*, vol. 16(1), pp. 20-28, Jan.-Feb. 2018.

[17] I. Mamounakis, N. Efthymiopoulos, P. Makris, D. J. Vergados, G. Tsaousoglou, E. Varvarigos, "A novel community pricing scheme for managing virtual energy communities and promoting behavioral change towards energy efficiency", Elsevier Electric Power Systems Research (EPSR), vol. 167, pp. 130-137, February 2019.

[18] DIRECTIVE (EU) 2018/2001 OF THE EUROPEAN PARLIAMENT AND OF THE COUNCIL of 11 December 2018 on the promotion of the use of energy from renewable sources.

[19] S. P. Rosado and S. K. Khadem, "Development of Community Grid: Review of Technical Issues and Challenges," *IEEE Transactions on Industry Applications*, vol. 55, no. 2, pp. 1171-1179, March-April 2019.

The smart grid actor called MicroGrid Operator (MGO) is a special case of the more general term "Energy Service Providers (ESPs)" that we have introduced within the FLEXGRID context. Without loss of generality, ESPs are smart grid stakeholders that dispose RES and/or flexibility assets and participate in the traditional energy markets and/or in local flexibility markets. In more detail, ESPs could be categorized in four major categories which are: i) RES producers/traders and/or RES aggregation service providers, ii) aggregators of loads from home electric appliances (e.g. HVAC, EVs, etc.) towards the provision of Demand Side Management (DSM) services, iii) owners and operators of BSS as well as providers of flexibility services through them, and iv) retailers, who just purchase energy from wholesale markets in order to serve the loads of their customers and thus may not possess any RES, DSM and BSS assets. Recently, ESPs compose hybrid business models, which means that they may fall in more than one from the aforementioned categories as extensively described in the use case scenarios' analysis of the previous FLEXGRID D2.1[20].

In the context of this work, we focus on a specific business case through which **an MGO entity efficiently represents the interests of local energy communities through the co-design and co-optimization of a set of services**. In more detail, the services that MGO operates on behalf of the local energy community are:

- optimal sizing, siting and operation for RES, Battery Storage System (BSS) and aggregated Demand Side Management (DSM) assets,
- modeling and management of distribution network through the use of optimal power flow algorithms in order to deal with local congestion and voltage control problems, and
- advanced models for the optimal MGO's participation in the existing energy markets.

According to the aforementioned innovative business case, the major contribution of FLEXGRID UCS 2.4 is the development of all the intelligence (i.e. mathematical modeling and algorithms) that this business model needs. In more detail, this work develops a holistic MGO's operational framework, which can concurrently:

- Coordinate the scheduling and planning of various types of flexibility assets, providing thus an integrated operation and investment tool for decision makers.
- Exploit Optimal Power Flow (OPF) algorithms, which take into consideration local congestion and voltage-related constraints and allow a network-aware RES and flexibility assets' exploitation policy.
- Co-optimize the operation of RES and flexibility assets and execute scenarios that facilitate the co-design of investments with their optimal mix.
- Model the competition in the day-ahead energy market and thus allow MGO to exploit the market competition. In contrast to the related literature that mainly considers large price-maker entities at the transmission system level, we showcase that MGO's profits can also be significant, despite the fact that its portfolio represents only a small portion of the market's total energy production/consumption. In this way, we assist energy islands and remote energy communities in order to mitigate their inherent RES-related and geographic-related negative externalities.

[20] https://flexgrid-project.eu/deliverables.html

6.2 Problem statement and summary of FLEXGRID research contributions

FLEXGRID proposes a network- and market-aware bidding strategy to co-optimize RES and flexibility asset usage in energy islands (or else remote local energy communities), which have a weak connection with the upper-level transmission network as well have weak connections within the distribution network (and especially the network edges).

In more detail, FLEXGRID proposes an MGO's operational framework, which can:

- Gradually decide the optimal mix of its RES and flexibility assets' sizing, siting and operation
- Respects the physical distribution network constraints in high-RES penetration contexts
- Bid strategically in the existing day-ahead energy market

In this way, energy cost in an energy island setting is minimized, where weak grid connections and unstable network operation in a high-RES penetration environment are considered. According to these, we also assumed that the local energy communities may opt for RES and flexibility asset investments instead of traditional network upgrade and reinforcement investments. Simulation results show ways that optimal and coordinated planning and scheduling of RES and flexibility assets can boost green energy investments.

It should also be noted that this work is closely inter-related to the UCS 2.2, in which optimal planning strategies are proposed that utilize stochastic and robust optimization models. It is also closely inter-related with UCS 2.3, in which optimal flexibility asset scheduling policies are proposed in order to maximize ESP's profits through participation in several energy, markets simultaneously, such as day-ahead, balancing, reserve and other novel distribution network level flexibility markets that are proposed by FLEXGRID.

6.3 System Model

Without harm of generality, this work considers a transmission grid that is characterized by a set of buses and a set of transmission lines. We also assume a Distribution Network (DN), which could be seen as a tree whose root is located at a given bus of the transmission grid (cf. outlined area in Figure 45 below). The DN is operated by a local DN operator or else MGO. The business case/model of the MGO is analyzed earlier in the introductory section[21]. According to it, MGO is responsible for controlling the BSSs and the flexible loads in order to strategically participate in the day-ahead energy market and in this way, it offers energy services with minimum cost to the local community and high financial sustainability for local RES operators.

The objective of the MGO is to use all its available local RES and thus avoid RES spillage. In addition, if the energy that the local RES produce is smaller than local demand, MGO buys energy from the main grid at the lowest possible cost. At the same time, the MGO has to

[21] The proposed model can be realized in all those small-scale DSOs that operate a rather vertical business in EU area (e.g. BNNETZE in southwestern Germany, non-interconnected islands in Greece and Croatia, etc.).

ensure the reliable operation of its network, which is a quite difficult task especially in future high RES penetration scenarios, where local RES curtailment should be kept at a minimum.

For example, as shown in Figure 45, a congestion problem may occur due to the weak connection linking the energy island/remote energy community with the main grid. Moreover, at the network edges, it is highly probable that various local voltage and congestion problems may occur frequently due to the expected high RES penetration levels and the rather weak connections within the local DN. The goal of UCS 2.4 is to calculate the MGO's optimal bidding strategy in the day-ahead energy market and the optimal schedule of the flexibility assets, while simultaneously taking into account the distribution network constraints.

The proposed system model is applicable to energy communities, cooperatives (i.e. RESCOOPs[22]), islands and municipal/local electric utilities, which own local RES, local flexibility assets and operate the local DN at the same time. In these cases, it is essential the facilitation of local and bottom-up RES and flexibility asset investments, which strengthen the energy autonomy and have lower costs in the long term. This is due to the fact that investments in stronger interconnection points with the main grid or local network reinforcements have higher financial cost and/or very high uncertainty due to bureaucratic procedures. In order to adequately present the advantages of the proposed business case, we evaluate two main RES penetration scenarios.

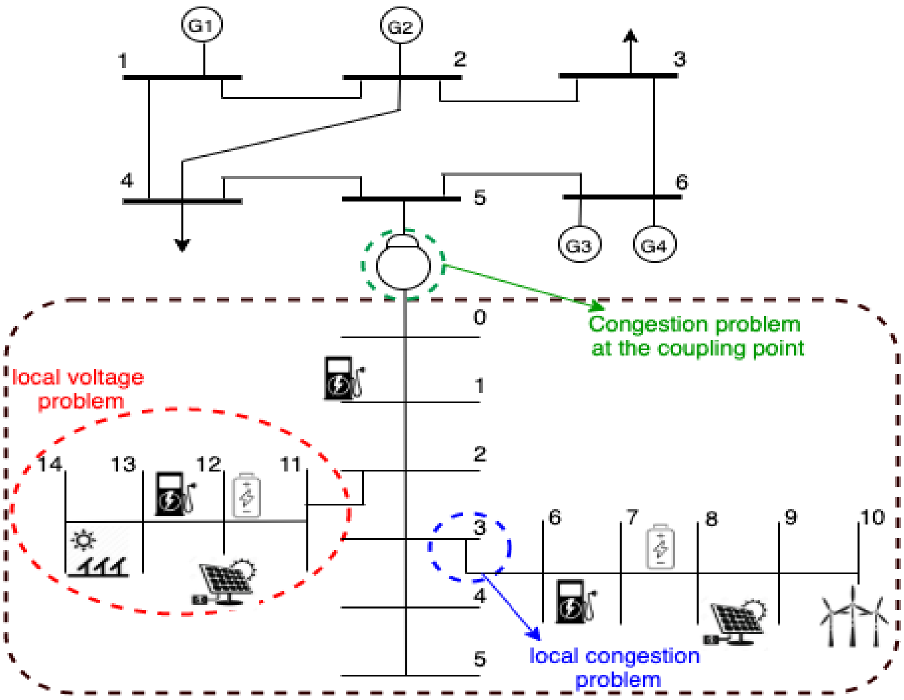

Figure 45: System model of UCS 2.4

1. [22] 'European federation of citizen energy cooperatives', https://www.rescoop.eu/, accessed 07 September 2021.

The first is the *high-RES penetration scenario*. Its objective is to eliminate local RES curtailment and achieve at the same time network feasibility (i.e. satisfy the constraints of the distribution network). Thus, this case is referred to as *network-aware bidding*.

On the second scenario, where RES penetration is low, we assume that demand cannot be satisfied by local RES. Thus, this case is dedicated in *market-aware bidding* to minimize energy costs. Both network- and market-aware bidding properties of the proposed framework are formulated below.

6.4 Problem Formulation

The MGO's decision process can be formulated as a bi-level problem[23], where the Upper-Level (UL) problem represents the minimization of MGO's energy costs and the Lower-Level (LL) one represents the market clearing process that derives the Locational Marginal Prices (LMPs) at the transmission network level. The generated Mathematical Problem with Equilibrium Constraints (MPEC) constitutes the MGO a price maker entity that is able to anticipate the electricity market's reaction to its decisions (quantity/price bids) and affect the system's marginal price. In order to model this process, a Stackelberg Game is formulated in which the MGO is the *Leader* and the day-ahead energy market clearing is the *Follower*. The problem is solved from the MGO's point of view that acts strategically. Hence, an Optimization Problem constrained by an Optimization Problem (OPcOP) is formulated, in which the UL problem is constrained by the LL problem.

6.4.1. Upper level (UL) problem – MGO minimizes its costs

In order for the MGO to schedule its flexibility assets in a network- and market-aware manner, its cost function is defined as:

$$\min_{X_U} \sum_{t \in H} \sum_{i \in N^G} \lambda_{i,t} \cdot p_{i,t}^{M} , \tag{1}$$

This optimization problem is subject to various constraints related to the operation of the: i) shiftable loads (i.e. DSM units), ii) BSS units, iii) DN, and iv) quantity bids. When a DN located at bus $i \in N^G$ supplies power to the main grid at timeslot t, it sells this power in the pool market at price $\lambda_{i,t}$,which is the nodal price (LMP) at bus *i*. In contrast, when a DN i draws power from the grid, it buys that power from the pool market at price $\lambda_{i,t}$. The amount of power to be sold or purchased at a specific bus and timeslot denoted as $p_{i,t}^{M}$ is a decision variable of MGO's problem.

6.4.2. Lower level (LL) problem – Market Operator (MO) minimizes social cost

The energy market is cleared by solving problem (1) in order to calculate the dispatches and the Locational Marginal Prices (LMPs). This minimizes the social cost, while accounting for: i) the transmission grid constraints, ii) the participants' quantity offers/bids and iii) price bids.

[23] S. Gabriel, A. Conejo, J. Fuller, B. Hobbs, and C. Ruiz, "Complementarity Modeling in Energy Markets", New York, NY, USA: Springer, 2013.

Thus, MO decides on the energy dispatch schedules of the market participants (generators, demand aggregators and MGO) by solving a DC-OPF problem:

$$\min_{X_L} \sum_{t \in H} \left(\sum_{i \in G} \left(c_{i,t}^{g} \cdot g_{i,t} \right) - \sum_{i \in D} \left(c_{i,t}^{d} \cdot d_{i,t} \right) + \sum_{i \in V^M} \left(c_{i,t}^{M} \cdot p_{i,t}^{M} \right) \right) \tag{2}$$

$$\text{s.t.} -g_{i,t} + d_{i,t} - p_{i,t}^{M} + \sum\nolimits_{j \neq i} y_{ij} \cdot \left(\theta_{i,t} - \theta_{j,t} \right) = 0, \forall i \in N, (i,j) \in L, t \in H, (\lambda_{i,t}) \tag{3}$$

$$g_{i}^{min} \le g_{i,t} \le g_{i}^{max}, \forall i \in G, t \in H, (\varphi_{i,t}^{gmin}, \varphi_{i,t}^{gmax}) \tag{4}$$

$$RD_i \le g_{i,t} - g_{i,t-1} \le RU_i, \forall i \in G, t > 1, (\varphi_{i,t}^{grd}, \varphi_{i,t}^{gru}) \tag{5}$$

$$RD_i \le g_{i,1} - g_{i,0} \le RU_i \ , \forall i \in G, (\varphi_{i,1}^{grd}, \varphi_{i,1}^{gru}), \tag{6}$$

$$d_{i,t}^{min} \le d_{i,t} \le d_{i,t}^{max} \ , \forall i \in D, t \in H, (\varphi_{i,t}^{dmin}, \varphi_{i,t}^{dmax}) \tag{7}$$

$$-b_{i,t} \le p_{i,t}^{M} \le o_{i,t} \ , \forall i \in N^G, t \in H, (\varphi_{i,t}^{mmin}, \varphi_{i,t}^{mmax}), \tag{8}$$

$$-T_{ij}^{max} \le y_{ij} \cdot \left(\theta_{i,t} - \theta_{j,t} \right) \le T_{ij}^{max}, \forall (i,j) \in L, i < j, t \in H, (\varphi_{ij,t}^{lmin}, \varphi_{ij,t}^{lmax}) \tag{9}$$

The decision variables of optimization problem (2) are: i) the power supply $g_{i,t}$ of each generator $i \in G$, ii) the power consumption $d_{i,t}$ of each demand aggregator $i \in D$, iii) the power supply/consumption $p_{i,t}^{M}$ of each DN and iv) the voltage phase angles $\theta_{i,t}$ at all buses $i \in N^G$ at timeslot t. The price bids of generators and demand aggregators at timeslot *t* are denoted by $c_{i,t}^{g}$ and $c_{i,t}^{d}$, respectively. Equation (6.3) expresses the power balance at bus *i* of the grid. The dual variables of these constraints provide the LMPs. In (3), y_{ij} is the admittance of transmission line $ij \in L$. Equation (4) refers to the generators' minimum and maximum capacity, while equations (5) and (6) express the constraints on the ramp up and down limits, denoted by RU_i and RD_i , respectively. Equation (7) refers to demand loads' upper ($d_{i,t}^{max}$) and lower bounds($d_{i,t}^{min}$), while equation (9) constraints power flow to the transmission lines' ij capacity limits (T_{ij}^{max}). Furthermore, constraint (8) enforces MO's decision concerning the power that is traded with the DNs to be not higher than the submitted offers/bids. The dual variables pertaining to each constraint of DC-OPF are specified in the parentheses following each constraint (Eqs. (3)-(9)).

Following up the descriptions of previous D4.2 (chapter 6), we further mathematically formulate our problem by modeling the following:

- Energy Storage Systems (ESS)
- Shiftable loads (DSM units)
- Underlying distribution network topology
- MGO's FlexOffers (i.e. quantity offers/bids)

The interested reader can see all the above-mentioned mathematical models in chapter 6 of D4.2.

6.4.3. Solution method

The formulated problem has a bi-level structure and has to be converted into a single optimization problem in order to be solved using a commercial solver. In our bi-level optimization problem, the constraining LL problem (6.2) is a Linear Program (LP) and therefore, Slater's condition holds[24]. Thus, DC-OPF problem's Karush-Kuhn-Tucker (KKT) conditions are necessary and sufficient optimality conditions (satisfy convexity and constraint qualification). Therefore, solving the DC-OPF is equivalent to solving its KKT conditions, which is a non-linear system of equations. As a result, the LL problem is converted into a set of non-linear constraints of the UL problem, and our problem becomes a single Mixed Integer Nonlinear Problem (MINLP). The non-linearities coming from the complementarity conditions (subset of KKT conditions) are tackled using the Big-M linearization method[25]. The non-linearities in the objective function are linearized using the Strong Duality Theorem applied to the LL problem. Finally, the initial bi-level problem is transformed into an equivalent single Mixed Integer Linear Problem (MILP), which can be easily solved using a commercial MILP solver.

6.5 Performance Evaluation Results

6.5.1. Simulation setup

In order to evaluate our proposed model and framework, we use a 6-bus test system with 4 conventional generators and 2 load buses. A 15-node radial DN is connected to bus 5 (cf. Figure 45). The transmission grid lines, generators and load data can be found in the research paper[26]. Loads are located on nodes 1, 2, 3, 4, 6, 7, 10, 11 and 12 of the DN. Load and line data for the DN are based on data[27] and can be found in our recent work[28]. We discretize the time horizon into 24 hourly timeslots. The interested reader can find extensive details about all the input data and performance evaluation results of this paper[29].

In the following, we consider two main case studies. The first case study called "high-RES penetration" considers a medium/long-term future context, in which the MGO will be required to make optimal RES and flexibility asset investments in order to maximize local

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[24] S. Boyd and L. Vandenberghe, *Convex Optimization*, Cambridge University Press, New York, 2004.

[25] J. Fortuny-Amat and B. McCarl, "A Representation and Economic Interpretation of a Two-Level Programming Problem", *The Journal of the Operational Research Society*, vol. 32(9), pp. 783-792, Sep. 1981.

[26] E. Nasrolahpour, J. Kazempour, H. Zareipour, and W. D. Rosehart, "Impacts of Ramping Inflexibility of Conventional Generators on Strategic Operation of Energy Storage Facilities", *IEEE Transactions on Smart Grid*, vol. 9(2), pp. 1334-1344, Mar. 2018.

2. [27] A. Gopi, P. Ajay-D-Vimal Raj, "Distributed generation for the line loss reduction in radial distribution system", in *Proc. 2012 International Conference on Emerging Trends in Electrical Engineering and Energy Management (ICETEEM)*, Chennai, India, 2012, pp. 29-32.
3. [28] K. Steriotis, K. Smpoukis, N. Efthymiopoulos, G. Tsaousoglou, P. Makris, E. Varvarigos, "Strategic and Network Aware Bidding Policy for Electric Utilities through the Optimal Orchestration of a Virtual and Heterogeneous Flexibility Assets' Portfolio", *Electric Power System Research, Elsevier*, vol. 184, Jul. 2020.
4. [29] H2020 FLEXGRID project Github repository. Available online at: https://github.com/FlexGrid/Network_and_Market-aware_bidding_EnergyIslands

RES usage (or else minimize local RES spillage) for the sake of its local energy community members. On the contrary, the second case study called "low-RES penetration" considers a shorter-term future context, in which the MGO is mostly interested in minimizing the energy cost of its local energy community by optimally scheduling its RES and flexibility assets through temporal arbitrage.

6.5.2. High-RES penetration case study

In this case study, we evaluate the network-aware bidding property of our model to maximize local RES usage. We assume that the MGO acts as a price taker in the wholesale energy market. This means that MGO schedules its RES and flexibility assets in a market-price-sensitivity agnostic manner. We also assume that local RES curtailment is not allowed so that feasibility of network flows is achieved in a zero local RES spillage context. It should be noted that the proposed model can also support an acceptable level of RES spillage (e.g. a maximum of 10% or 20% of nominal RES capacity to be curtailable), which is the today's Business-As-Usual process in a straight-forward manner.

6.5.2.1. Impact of RES and flexibility assets' siting in the DN

In this subsection, we study the impact of RES siting in the MGO's flexibility assets' investment decision. First, we consider 2 cases for the locations that the RES units will be installed within the distribution network. In the first case, we consider nodes 2, 8, 11 and 13 for RES installation (i.e. non-critical location case), while in the second case, we select nodes 2, 5, 10, 11 and 13 (i.e. critical location case). By the term *"critical location"*, we mean that intermittent and variable RES assets are sited at the edge nodes of the network (i.e. nodes 5 and 10) incurring thus greater problems in terms of local congestion and voltage management. We consider both types of RES (i.e. PVs and wind turbines). In both cases mentioned above, we have selected nodes 5, 8, 10 and 13 to install identical BSSs and we assume that a part of loads in nodes 2, 3, 4, 6 and 7 are flexible, resulting in a total capacity of 1MW flexible load. This load is assumed to operate during the peak hour (i.e. 18:00); however it can be shifted from 16:00 to 20:00. In each one of the two aforementioned cases, we examine two sub cases. In the first one, the nominal RES capacity is 1.5 times higher than the nominal peak load, while in the latter case, the nominal RES capacity is 2 times higher than the nominal peak load. The two subcases are noted in the Figure 46 below as 150% and 200% RES penetration respectively.

The following figure depicts the financial balance (profit/deficit) that MGO has as a function of BSS size. BSS is needed in order to keep the distribution network within its operating limits and avoid in this way RES spillage phenomenon. Note that the size of BSS highly depends on the siting and the sizing of the RES units (which is depicted and handled as an input parameter in the two subcases). In the figure below, zero financial balance implies infeasible distribution network operation. In other words, the MGO will have to pay the very high Value of Lost Load (VOLL) for all the time that the network is in an unstable condition. Positive and negative financial balance implies that MGO has profits and deficit respectively. In the Non-Critical location case and for 150% RES penetration, MGO needs to install at least 375 kW of total BSS power capacity in order to safely operate its network, while for 200% RES penetration, it needs to install at least 13,130kW BSS. In the critical location case and in the subcases of 150% and 200% RES penetration, the MGO has to install at least 8,375 and 21,880 KW of BSS power capacity respectively. We see that, in these specific setups and under both the Non-Critical and Critical location cases, 200% RES penetration requires the most BSS power capacity and leads to more market profit for the MGO, but this comes at the expense of higher BSS investments. Given the very high VOLL, the eligible distribution network nodes to put more RES units in the future are the ones in the "non-critical" case. This is quite important for the MGO's business model in order to be able to prioritize the installation of its future RES and respective flexibility assets in the correct nodes of the distribution network.

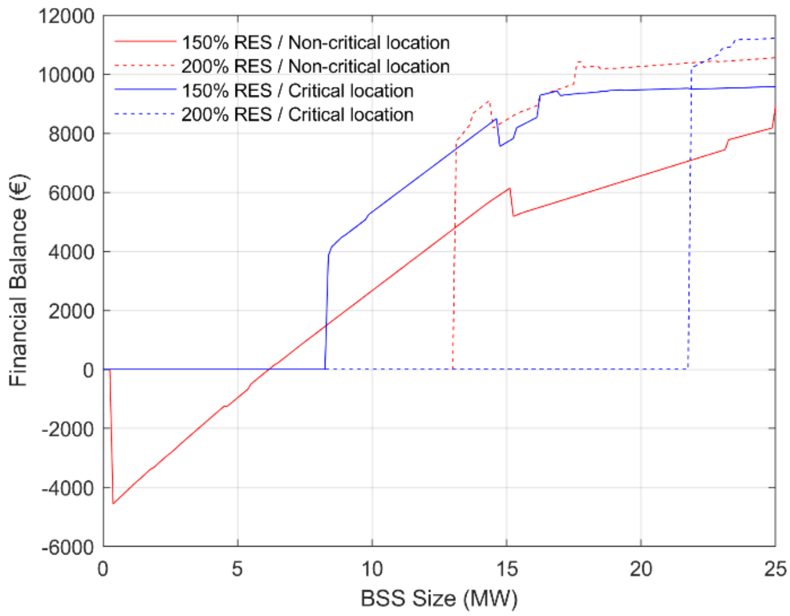

Figure 46: MGO's financial balance as a function of BSS size for critical and non-critical DN locations cases under two RES penetration subcases

6.5.2.2. Impact of RES and flexibility assets' sizing

As far as it concerns the impact of the RES sizing on the MGO's financial balance and based on siting results from the figure above, we select the eligible RES sizes in order to have network feasibility outcomes (i.e., we do not consider the RES sizes that produce DN infeasibilities above a certain and widely accepted probability). Thus, we continue only with the *"non-critical location"* network case presented above, as it would not be useful to consider infeasible network setups (which takes place in critical location case), where the MGO's investment costs on flexibility assets would be huge.

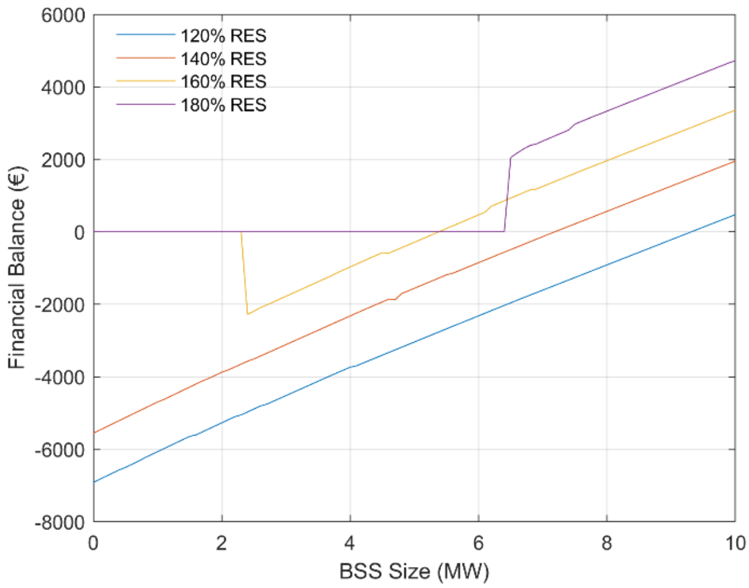

Figure 47: MGO's financial balance as a function of BSS size for different RES sizes under the non-critical locations case

The next step is to examine the financial outcome for the MGO (either profit or deficit) under 4 high-RES penetration scenarios. In more detail, the figure above depicts the financial balance of the MGO as a function of the installed BSS power capacity under 120% (cf. blue line), 140% (cf. red line), 160% (cf. yellow line) and 180% (cf. purple line) RES penetration scenarios (note that zero values of financial balance imply network infeasibility). As expected, based on the results of the previous subsection, for RES penetration up to 140%, the distribution network can operate safely even without (i.e., zero) BSS installations, but with 1MW flexible load capacity (see non-zero financial balance values for all BSS size values). Of course, MGO's financial balance increases linearly as the BSS size increases, too. For 160% RES penetration, the minimum total BSS capacity that is needed to ensure zero RES spillage is 2,400 kW, while for 180% RES, the minimum BSS power requirement is 6,500 kW. An MGO can reduce its daily operating cost by installing centralized BSSs or aggregating distributed residential storage units. The first business choice entails upfront flexibility investment costs for the MGO, but the advantage is that that the MGO's operational costs are minimized. On the other hand, the aggregation of multiple small-scale and distributed flexibility assets means that the investment costs will be (mostly) paid by the end users; however large operational expenditures are expected for the MGO, because it has to communicate and coordinate the flexibility aggregation process with multiple and heterogeneous S/W agents and H/W infrastructures/end user installations. In order for a price taker MGO to make profits by selling energy to the grid, a significant amount of investment has to take place. For example, for 160% RES, a 5,400 kW BSS power capacity is needed. This is very important for the MGO, who can easily measure the CAPEX (i.e., capital expenditures) versus OPEX (i.e. operational expenditures) trade-off in order to incorporate this type of calculations in its business 91odelling process.

6.5.2.3. Optimal flexibility assets' sizing and scheduling

We now proceed to find the optimal flexibility asset size to maximize MGO's profits for a few RES penetration setups. As already seen, for the specific RES and flexibility assets' siting, up to 140% RES penetration is safe for the network to operate within its limits. Thus, we now examine 3 more conservative subcases of RES production, namely 100%, 120% and 140% RES penetration.

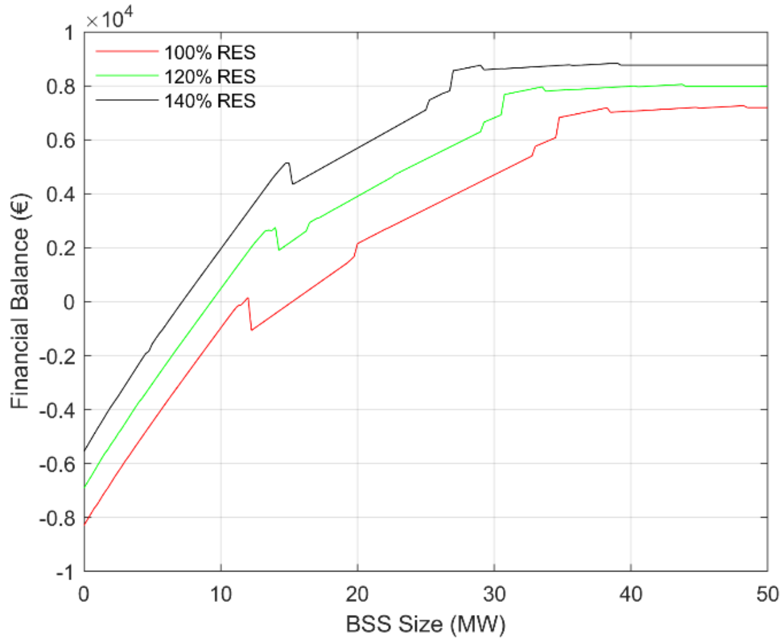

Figure 48: MGO's financial balance as a function of BSS size (optimal FlexAsset sizing to maximize MGO's profits)

The figure above depicts MGO's financial balance as a function of BSS under the three aforementioned subcases. From this figure, one may observe that, in all RES penetration cases, the MGO's financial benefit increases with the total power capacity of BSSs, up to a saturation point. Intuitively, this is the optimal BSS sizing. Beyond this BSS size, the MGO does not gain any more profit, corresponding to an over-investment context that should be avoided by the MGO. It is highlighted that in the higher RES penetration subcase, the MGO's profits stop increasing for less BSS capacity (29,000 kW) than in the other two subcases (33,500 and 38,000 kW for 120 and 100% RES penetration respectively). This is because the less RES production capacity is installed in the distribution network, the more the flexibility assets are dispatched in order to maximize MGO's profits by employing temporal arbitrage.

6.5.3. Low-RES penetration case study

So far, we have only examined high-RES penetration cases that will most probably appear in some years from now. But how could a MGO lower its energy costs today where it possesses a relatively low amount of local RES and flexibility assets and it mostly draws power from the higher-level transmission grid? Therefore, we now evaluate the market-aware bidding property of our model to minimize energy cost in a more realistic today's low-RES penetration scenario. In this scenario, the MGO is a price-maker market entity (i.e., we model the affection in the prices of the wholesale energy market that MGO's bidding policy has). We compare the price-maker algorithm to the price taker solution. In more detail, the figure below depicts the MGO's cost under six network setups with low-RES penetration (in this case study, the financial balance is always negative and we note it as "MG cost"). In the first three network setups of the following figure, we assume 80% RES penetration and in the last three, 60% RES penetration. In setups 1 and 4, MGO decides to invest only in DSM (i.e. 35% of the nominal peak load can be shifted) and not at all in BSSs. In setups 2 and 5, the MGO has 500 kW of BSS power installed and 30% of the nominal peak load DSM capacity. Finally, in setups 3 and 6, the installed BSS power capacity increases to 2,000 kW, while the DSM capacity remains 30% of the nominal peak load. As can be seen in the figure below, our algorithm outperforms the price taker solution in every setup by an average percentage of 8% in terms of the MGO's energy cost. This indicates that, even if its portfolio represents a small portion of the wholesale market, the MGO can achieve a significantly smaller energy cost by acting strategically and implementing our proposed model, as opposed to adopting the price taker solution.

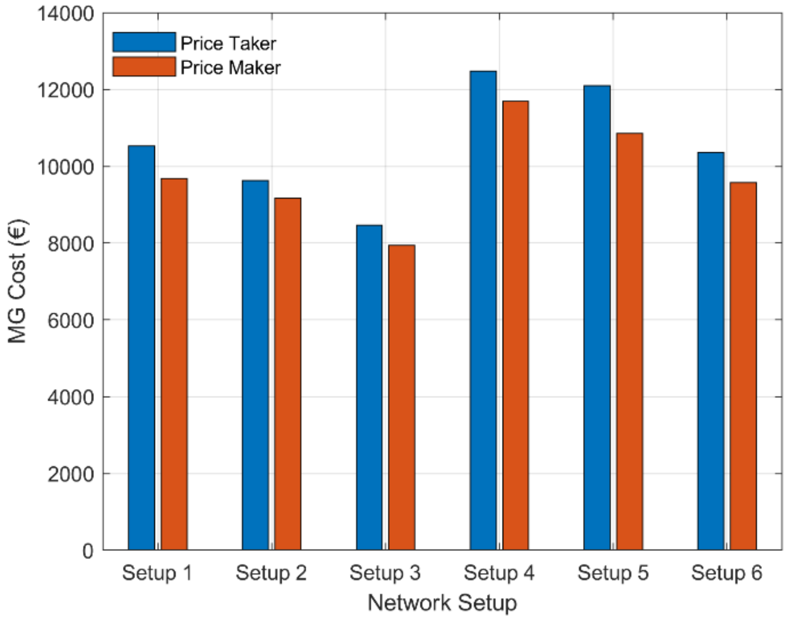

Figure 49: MGO's costs (Price taker vs. price maker bidding)

6.6 Lessons learnt and roadmap towards Horizon Europe 2021-2027

In FLEXGRID UCS 2.4, we dealt with the increasing RES penetration in today's energy islands and rural energy communities with weak grid connections, which is expected to incur severe distribution network stability problems (i.e. congestion, voltage issues), especially when RES spillage minimization and energy costs' minimization for the local energy community are set as major pre-requisites. In UCS 2.4, we consider a Microgrid Operator (MGO) that:

- gradually decides the optimal mix of its RES and flexibility assets' sizing, siting and operation,
- respects the physical distribution network constraints in high RES penetration contexts, and
- is able to bid strategically in the existing day-ahead energy market.

After communicating FLEXGRID UCS 2.4 scientific results to both academic and industrial communities, we have come up with a short list of lessons learned that could be further investigated in future R&I initiatives. The Table 13 summarizes research and business-related insights for each one of the lessons learned.

Table 13 - Lessons learnt for UCS 2.4

Lesson learned	Research & Business insights
Coordinated planning and scheduling of RES and flexibility assets may result in better scientific results, but a gradual decision-making process (e.g. yearly updates) by the MGO is also required for real-life applicability.	Use of stochastic optimization modeling is required to account for several future RES and demand curves as well as future flexibility availability (cf. UCS 2.2 results). MGO should run the proposed solution periodically to fine-tune its RES and flexibility investment decisions for the years ahead.
MGO/energy community should be able to prioritize the installations of new RES and FlexAssets in the "most appropriate" nodes of the DN or else the investments will be economically unsustainable and the local RES usage will not be efficient.	Investments for DN upgrades should be coordinated with DN-level RES and flexibility investments. Interaction between TN-level and DN-level planning processes is required in order to avoid over/under-investment phenomena.
It may be useless to achieve high RES penetration levels in a local area without being backed up with the required local flexibility, because this will cause high operational costs due to lost load and/or lost renewable energy (cf. RES curtailments).	Local RES and flexibility investment planning should go hand-in-hand. One solution is to have available flexibility (i.e. battery) together with each new installed RES asset. Another more efficient solution is for the MGO to strategically decide where and how much flexibility to install in its network.
Need to smoothly and carefully proceed to the energy transition phase without causing more problems (i.e. energy cost increase, instability issues, under-utilization of newly installed RES).	There is no "one size & site fits all" solution for every energy community/island/microgrid. Additional local needs/peculiarities/ comparative advantages should be taken into consideration for policy making.
Need to calculate the VOLL and value of lost Renewable Energy vs. the RES/flexibility investment cost both in the short term (i.e. reliable DN operation) and in the long term (with respect to EU agenda's targets)	A sophisticated techno-economic analysis is needed by the local DSO (or MGO) to decide the optimal trade-off between network upgrades and flexibility procurement.
The MGO's financial benefit increases with the total power capacity of BSSs, up to a saturation point. Intuitively, this is the optimal BSS sizing. Beyond this BSS size, the MGO does not gain any more profit, corresponding to an over-	Coordinated actions should take place between a portfolio of FlexAsset investors (i.e. end prosumers and/or profit-based companies) and the local network operator. These actions should

investment context that should be avoided by the MGO.	also be effectively communicated to the upstream network operator, too.
In higher RES penetration scenarios, the MGO's profits stop increasing for less BSS capacity. In other words, the less new RES production capacity is installed in the distribution network, the more the flexibility assets are dispatched in order to maximize MGO's profits by employing temporal arbitrage.	A thorough cost-benefit analysis is needed in order to find the optimal mix between RES and flexibility investments.
Even if an MGO's portfolio represents a small portion of the wholesale market, the MGO can achieve a significantly smaller energy cost by acting strategically and implementing a market-aware bidding strategy, as opposed to adopting a "price taker" solution.	Research on new policy measures to support green investments from energy communities at EU scale and especially at the edges of the energy network.
Accurate FlexAsset modeling can significantly change the planning/scheduling results. The problem is that current models produce too optimistic results that may have large negative impact on flexibility investment decision making.	More accurate FlexAsset (i.e. battery storage system) modeling is needed that is much closer to real-life operation of these flexibility assets (cf. UCS 2.1 results).
Need to elaborate on optimal flexibility assets' scheduling policies in order to maximize profits through participation in several energy markets simultaneously, i.e. not only day-ahead energy but also balancing, reserve and other emerging distribution network level flexibility markets such as the ones proposed by FLEXGRID	Co-optimize participation in several markets simultaneously (cf. UCS 2.3 results).

7 Independent large FlexAsset Owner leases Storage for several Purposes to several Market Stakeholders (UCS 2.6)

This chapter deals with the research problem of UCS 2.6. The idea of this UCS is to propose concepts and ideas, where storage (capacity and power) may be leased for an agreed period of time. In that manner, an ESP user may form new business strategies and lighten their financial burden. Rather than buying energy storage systems, the ESP would have the opportunity to lease exactly the required capacity and power. Large FlexAsset Owner would benefit from lease agreements with several market stakeholders without the need to actively participate in the electricity markets.

7.1 Summary of FLEXGRID research results so far

High RES penetration, orientation towards the decentralized paradigm and active prosumers bring intermittency and uncertainty into the system. This raises the importance of DERs, bidirectional flow management and energy storage systems. Especially energy storage systems and their possibility of the temporal arbitrage offer solutions to: i) secure stable power supply in high RES penetration scenarios, ii) develop new business strategies and iii) accelerate the transition towards green energy solutions. Although their price has fallen, the acquisition of such systems may still present quite a financial burden. Hence, many projects might be (temporarily) stopped if an interested party lacks financial power to finance the needed capital investments. To lighten capital-intensive projects, and to stimulate projects that aren't even economically viable under the current prices of the energy storage systems, the idea of this use case is to propose concepts and ideas where storage (in terms of capacity and power) may be leased for an agreed period of time. This approach aims to: i) lower power market financial entry barriers, enable the development of innovative business models and iii) stimulate greater utilization of the energy storage systems. The whole idea is inspired by the term "sharing economy". The sharing economy is an economic model defined as a peer-to-peer (P2P) based activity of acquiring, providing, or sharing access to goods and services that is often facilitated by a community-based on-line platform [15] . Very thorough and easy to read introduction to utilization of this concept in the world of energy storage systems is given by Lombardi et al. [16]. They introduce the concept, explain what energy storage systems are nowadays used for, what characterizes different technologies and how to incorporate all of that into a suitable and profit increasing economy sharing model. Scientific articles covering and analyzing the idea of a concept where some large FlexAsset owner (e.g. battery owner) leases storage to the interested parties is not extensive. But we have identified research efforts and publications that have been done following similar direction. Liu et al. [17] proposed a model where centralized storage facilities, owned by facility operator provide decentralized energy storage services to the interested parties. Benefits of such approach are:

- Using the advantages of the economies of scale
- Storage units are easier to manage (physically) when they are centralized

The authors got the motivation to utilize this concept from cloud computing services. They named the concept – Cloud Energy Storage (CES), presented how to realize it, explained the business model and emphasized the following pros of such an approach:

- CES leverages the diversity in the users' demand for storage
- CES is able to better schedule the battery because it has more information than an individual user
- Economies of scale
- Diverse portfolio of storage technologies

[18] extends the previous article. It divides the services into energy capacity and power lease, showing how such model could help in reducing overall electricity prices. CES concept is also used in [19]. The authors have proposed a bilevel model for optimal energy storage capacity pricing and sizing. CES operator makes capacity pricing and sizing decision in the upper level, while the lower level presents consumers' renting and operating decisions. A case study has been conducted on 100 household consumers in Ireland and CES concept has been recognized as an effective business model. [20] has expanded the CES concept even further, using perfect and imperfect information models to evaluate the behaviour of CES participants under respective information model types. The case study based on actual Irish consumer load profiles and prices has showed the following:

- The unit capital of cost of energy storage has a significant effect on the value and profitability of CES
- The imperfect estimation of consumer behaviour would lower the profitability of CES
- The economies of scale of large storage facilities make CES more profitable

A concept where distribution companies own storage and lease the battery capacity to the customers is proposed by Motyka [21]. DSO may use the batteries to over the consumption when renewables are not producing enough power to satisfy the demand. Such approach may result with lower transmission losses and minimization of the consumption peaks, but correct sizing of the batteries in respective node is a delicate and important task.

Authors in [22] presented a two-stage optimization problem to model the interaction between a storage aggregator and users. The aggregator virtualizes its energy storage into separable virtual capacities and sells them to the interested parties. Stage 1 of the problem is dedicated for the aggregator to determine the investment and pricing decisions, while stage 2 enables each user to decide the virtual capacity to purchase together with the operation of the virtual storage. Authors argue that their model can reduce the physical energy storage investment of the aggregator by 54.3% and reduce the users' total costs by 34.7%, compared to the case where users acquire their own physical storage. The concept of Virtual Energy Storage System (VESS) is used in [23]. The authors demonstrate how VESS aggregates various controllable components of energy systems (conventional ESS, flexible loads, distributed generators, microgrids, local DC networks and even multi-vector energy systems). Those aggregated entities act on the markets as a single unit with specific characteristics. The authors showed on the example of VESS formed of domestic refrigerators and flywheel energy storage systems power system frequency response, taking care of the lifetime of the aggregated units.

In addition to the published scientific articles, similar concepts are already introduced in the private sector. Green2store [30] gathers a number of distributed energy storage units from users to form a large storage facility on the cloud to provide service for energy storage users, while Sonnenbaterie [31] installs batteries on users' location but ordinates them in a centralized fashion.

7.2 System model

This work proposes two concepts with similar goal – energy storage capacity and power lease. Although two concepts differ in many characteristics, besides the similar goal, they share also similar benefits for the involved players. From lower market entry barriers, incentivizing energy storage systems utilization, accelerating RES penetration to raising social welfare.

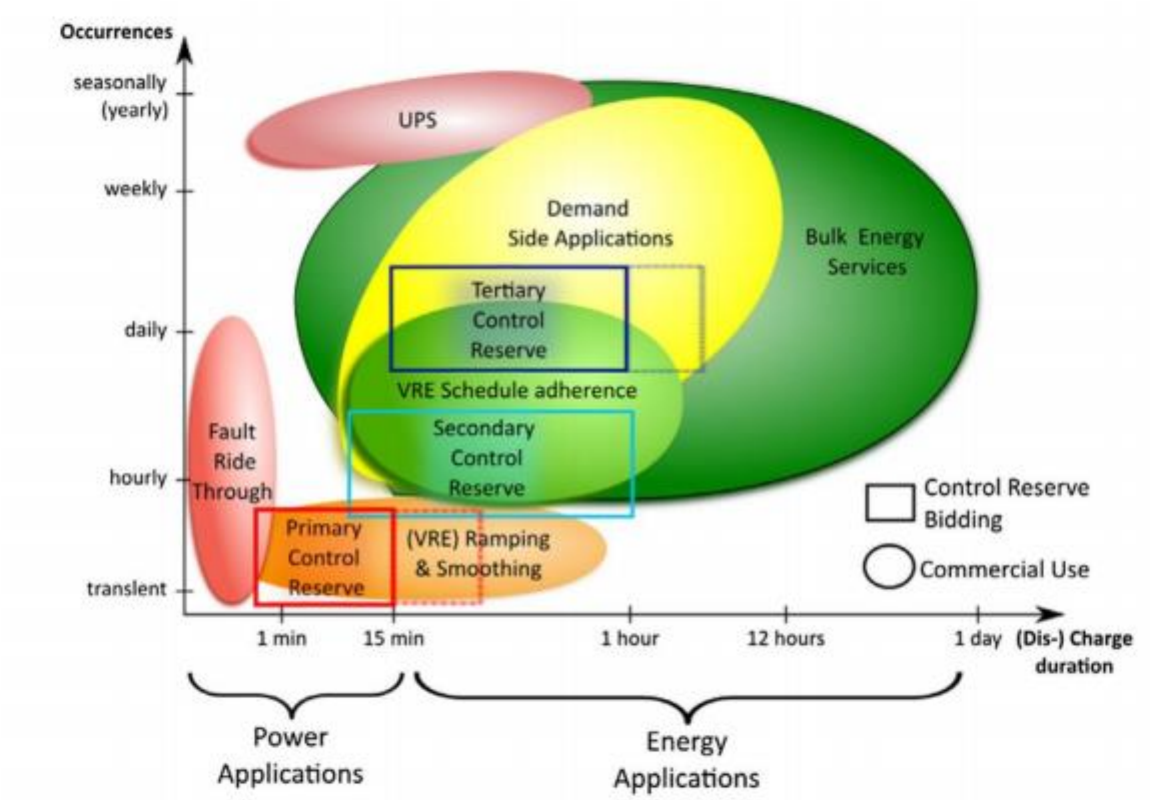

Figure 50 - Average rate of occurrences and the typical charging/discharging duration [16]

The main idea of the first approach lies in the interaction between a large FlexAsset owner that wants to lease its storage capacity/power and a user willing to procure such service instead of making capital investments in new assets. For the concept to be generally accepted, all interested parties should feel the benefits of participating in it. Large FlexAsset owner should generate stable income by leasing its storage capacity and not caring (explicitly) about the actualities in the electricity markets (e.g. day-ahead market prices). On the other hands, interested parties that want to participate in the electricity markets with storage units but postpone (or avoid) capital investments, may find the right solution in procuring energy storage capacity/power from a FlexAsset owner. Important assumption is

30 https://www.offis.de/offis/projekt/green2store.html

31 https://sonnengroup.com/sonnenbatterie/

that the FlexAsset owner may acquire energy storage systems under lower prices due to the volume of the order (greater discount). Furthermore, FlexAsset owner may acquire various technologies and consequently offer greater flexibility of features while meeting customer preferences. Meaning that the user that procures such service should not only benefit from the lower prices, but also from diverse energy storage characteristics. In that manner, FlexAsset owner needs to take care about siting, sizing, technology mix and prices of its energy storage portfolio. Figure 50 nicely illustrates how users may for different purposes have different storage needs

7.3 Problem formulation

In the subchapter 7.2, two approaches have been discussed. One where the main research problem is the interaction between large FlexAsset owner that leases storage to the several market stakeholders, and the other where the SMO acts in a similar manner like Airbnb linking energy storage systems supply and demand. In the scope of this use case scenario, the focus will be more on the first concept. Nevertheless, both approaches will be investigated and then compared.

To model the interaction between the large FlexAsset owner and user(s), bilevel model programming will be used. Upper-level deals with the large FlexAsset services offering and investment, while the lower level problem models the players who are keen to procure such services.

The second concept is based on peer-to-peer business model where SMO is a matchmaker between group of entities that offer energy storage capacity and power services, and other keen to procure it. The main task of the SMO is to provide the trading platform, regulations and procedures. Moreover, algorithmic solution should deal with price forming possibilities and matching the ones offering the service with other wanting that service.

7.4 Lessons learnt and roadmap towards Horizon Europe 2021-2027

In FLEXGRID UCS 2.6, we have analyzed independent large FlexAsset Owner who may lease its storage for several purposes to several market stakeholders. The idea is for a user rather than buying energy storage systems, to have the opportunity to lease exactly the required capacity and power. Large FlexAsset Owner would benefit from lease agreements with several market stakeholders without the need to actively participate in the electricity markets. Although the final model is still not done, in the following months the clearer concept model should be done and more detailed mathematical formulation followed by simulation results.

Nevertheless, initial scientific findings have been discussed to both academic and industrial communities. Following table summarizes research and business-related insights for each one of the lessons learned.

Table 14 - Lessons learnt for UCS 2.6

Lesson learnt	Research & Business insights
Storage facilities require high CAPEX, hence a lot of projects fail the cost benefit analysis	Bypass of CAPEX could pave the way for many new business opportunities and novel strategies, hence future research should focus on finding and formulating feasible methods that may be used in the real-life situations
Battery storage units lease model success is highly dependent on the accurate monitoring of the state of energy	For the large FlexAsset owner to be able to take the advantage of the lease model without creating and accepting unfeasible offers, it is of the utmost importance to have a clear vision of the battery storage unit characteristics and its condition. Accurate battery modelling is thus required so the agreed contracts are indeed feasible.
Users require both energy and capacity lease models	Different types of user are more prone to either energy or capacity reservation models, hence future research should also address both directions and their combination
There are already some active pilot projects based on virtual storage units. Meaning, that various stakeholders understand possible benefits of such model.	Industry has recognized potential benefits of the virtual storage models. Further cooperation between academia and industry could be extended on the experience gathered in the ongoing pilot (and commercial) projects
The idea may be realized in various forms, i.e. in this chapter two considered directions are mentioned.	Future work should closely analyse pros and cons of both approaches and discuss between academia and industry which approach has greater practical potential to realize it a t higher TRLs.

9 Conclusion

ESP, a profit-oriented company, which may enter into contractual arrangements with various types of flexibility assets was the main point of interest of the WP4 work efforts. Within WP4 of FLEXGRID, the focus of research was on the development of a S/W tool, namely FlexSupplier's Toolkit (FST), that is intended to help utilizing FlexAssets in an optimal manner. It includes market and PV forecasting, together with models and algorithms to optimize ESP's market behaviour in a holistic way (e.g. via optimal scheduling, bidding, siting and sizing models and algorithms). Different approaches and use case scenarios were investigated reflecting different types of market designs, namely different proposals of the potential DLFM. Concluding remarks, lessons learned and research and business insights for each approach are summarized in the final sections of chapters 2, 3, 4, 5, 6 and 7.

The research work of WP4 will be used and integrated within the FST and FLEXGRID ATP (WP6). More specifically, versions of the algorithms of UCS 2.1 – "ESP's OPEX minimization", UCS 2.2 – "ESP's CAPEX minimization" and UCS 2.3 – "ESP's profit maximization" are now being integrated within the ongoing work of WP6. These FLEXGRID services will facilitate the ESP towards creating optimal strategies to improve its market position and allow both online operation for real-time support and offline operation for "what-if" simulations and testing under different scenarios.

The research results of all use case scenarios of WP4 are Key Exploitable Results (KERs) of the FLEXGRID project and the research outcome will be used for the final development and enhancement of the business models and value proposition regarding the ESP.

In the figure below, the timeline schedule of WP4 is illustrated. Milestone #9 has been achieved with this deliverable, which concludes all milestones of WP4.

Figure 51 - FLEXGRID project's and WP4 timeline schedule

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