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Glossary of Acronyms

Project management terminology

Acronym	Definition
D	Deliverable
HLUC	High Level Use Case
KPI	Key Performance Indicator
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
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
IEA	International Energy Agency
ICT	Information and Communication Technology
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
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 intermediate version of the mathematical models, research problem formulations, algorithms and performance evaluation results for the support of innovative business models for ESPs and RESPs.

Table 1: Document History Summary

Revision Date	File version	Summary of Changes
30/11/2020	v0.1	Draft ToC circulated within all consortium partners
08/12/2020	v0.2	WP4 agreement on the final ToC and writing task delegations per partner
13/01/2021	v0.3	Final ToC version has been presented to the FLEXGRID consortium
08/03/2021	v0.4	WP4 partners contributed their 1st round inputs and first draft version has been reviewed by DTU.
15/03/2021	v0.6	WP4 partners addressed internal review comments and contributed their 2nd round inputs.
29/03/2021	v0.9	UNIZG-FER addressed all comments from the internal review process and forwarded the final version to the coordinator.
31/03/2021	v1.0	Coordinator (ICCS) made final enhancements/changes and submitted to ECAS portal.

Executive Summary

This report is an official deliverable of H2020-GA-863876 FLEXGRID project dealing with the detailed architecture design of all 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 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 architecture. The respective algorithms (e.g. algorithms from UCSs 2.1, 2.2 and 2.3) will be implemented in a S/W toolkit (FST), which will dynamically interact with the core FLEXGRID ATP.

Chapter 1 is an introduction of this report summarizing the scope and purpose of the document. More specifically, it provides a high-level description and summary of: i) the ESP's business interests and how these are inter-related with the residual FLEXGRID business ecosystem, ii) state-of-the-art solutions for the ESP's business challenges, iii) proposed research problems' statements, which are based on (i) and (ii), and what is the FLEXGRID's innovations, and iv) FLEXGRID's potential research impact on future aggregator's business.

Each one of chapters 2-7 follows a similar structure in order to present the WP4 research results in a coherent manner. In particular, for each one of the six respective research problems, we present:

- Problem statement, related state-of-the-art and summary of FLEXGRID research contributions
- Proposed system model under study
- Problem formulation including all mathematical modeling
- Proposed algorithmic solution
- Simulation setup and performance evaluation results
- Next steps on how to elaborate on the ongoing WP4 research work until M26

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, a part of the HLUC04_UCS04, that will be provided to the ESP and aggregator actors, 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, a Reactive-DLFM architecture is considered, as this version may be easily added to the current market paradigm without any major modifications.

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 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[1], 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 radial 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.

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**.

[1] https://nodesmarket.com/

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.

Chapter 8 presents **how all the above-mentioned research novelties that have been tested and validated at TRL 3, will be integrated in the FlexSupplier's Toolkit (AFAT), which is part of the FLEXGRID Automated Trading Platform (ATP) at TRL 5**. In particular, the FST's frontend and backend services are described as well as the interaction between the WP4 research work and WP6 S/W implementation and integration work.

Finally, in Chapter 9, we summarize the next steps for WP4 research work. We also describe how the WP4 research results will be elaborated on in other Work Packages until the end of the project's lifetime.

1 Introduction

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

The purpose of High Level Use Case (HLUC) is the development of advanced flexibility management services for the profit-oriented Energy Service Providers (ESPs). An ESP is, per definition in D2.1[2], 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. Including advanced forecast methods both for market prices and RES generation (emphasize on PV), 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). Deliverables D2.1 and D2.2 documented respective Use Case Scenarios (UCSs), which encompass the above mentioned features.

HLUC #2 focuses on the participation of the ESPs on various markets, including the proposed Distribution Level Flexibility Market (DLFM). Furthermore, interaction between ESPs (as providers of the flexibility) and TSOs/DSOs as well BRPs (as flexibility buyers) is established through offering and bidding for various types of (flexibility) services. It is important to add that the ESP is not constrained only on providing flexibility services, but it may participate in all common markets (e.g. day-ahead energy market).

In the previous deliverable, D4.1, five research problems have been clearly defined. Besides four research problems that are an integral part of WP4 efforts, one research problem (market and RES forecasting) is also analysed as part of the WP3 efforts. A high-level description of the mentioned problems has taken place together with the related works from the international literature. FLEXGRID's research contributions have been clearly defined and preliminary thoughts 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.

This deliverable elaborates on the results of D4.1 by presenting the mature version of mathematical modelling and proposed algorithms, while initial performance results are presented, too. Our next goal for M19-M26 period is to finalize algorithms where needed, perform more simulations considering more realistic case studies and using real-life datasets by following the FLEXGRID data management plan.

1.2 Summary of state-of-the-art solutions for the ESP's business challenges

In the previous D4.1, as part of every chapter dedicated to respective research problem, an extensive survey on related works in the international literature has been made. Although all research problems are intended to provide added value for the profit-oriented ESPs, surveys concerning market and PV forecasting have been conducted in a more general manner (as

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

their benefits are applicable in other work packages too), while surveys from the other use case scenarios consider the problem in a more ESP-specific manner.

In D4.1, Task 13 of the International Energy Agency (IEA) Photovoltaic Power System (PVPS) is considered as the state-of-the-art study on solar forecasting. It shows that available PV power production forecasts from the most third-party organizations are acquired either from measured resources or outputs from NWP models that can primarily be used for weather forecasts. While market price forecasting survey was divided into two parts – a) about trading mechanisms which exist in each market and the interactions between the different markets and b) about mathematical models and techniques for predicting electricity prices in the Day-Ahead Market/Auction Based Markets. As one of the most promising price forecasting tools, Extreme Learning Machine (ELM) was pointed out. Hence, the ELM algorithm was selected as the fundamental algorithm to be developed further for forecasting needs.

Surveys regarding other use cases, those dealing with optimal market appearances, may be divided in the following manner:

- Optimal scheduling problems
- Optimal bidding strategies
- Optimal siting and sizing methods

In the center of them all, FLEXGRID WP4 puts the profit oriented ESP. Available literature concerning scheduling algorithms considers independent scheduling of specific assets such as Battery Storage Units (BSUs), which are becoming integral parts of the modern network systems, but also coordinated scheduling of complementary assets (e.g. BSUs and wind farm) as they may mutually benefit from such scheduling. Two main categories for ESP’s revenue modelling have been identified, namely price-taker and price-maker models. Price-taker models assume that the ESP cannot affect prices on respective markets, meaning that its actions do not affect the market (its relative market share is not significant). Bilevel programming has been used to model the latter one, but with the important notice that such problems need to be transformed into a form suitable for currently available solvers. For instance, they can also be recast as a single-level problem depending on type of the problem. Furthermore, it has been noticed that most of the network-aware models use DC-OPF model, instead of the computationally more burdening (but more precise) AC-OPF. But as the focus is shifting towards the distribution networks, AC-OPF is gaining more and more importance because it encompasses important occurrences in such networks, namely network losses and voltage deviations which the approximate nature of DC-OPF neglects. Literature concerning optimal siting and sizing mostly considers energy storage systems with the distinction whether the problem is observed on the transmission or distribution level. Such problems are sometimes also considered alongside network expansion plans as a measure of possible deferral of the high capital investment costs.

1.3 Summary of research problems and FLEXGRID’s research innovation

Following up the survey work briefly mentioned above from both academic and industrial perspectives, this deliverable describes five main related FLEXGRID research problems:

- Market prices (cf. UCS4.4) and RES (PV) forecasting

- The ESP user wants to minimize its operational expenditures (OPEX) by optimally scheduling FlexAssets (cf. UCS 2.1)
- The ESP user wants to minimize capital investments (CAPEX) by using optimal siting and sizing algorithm (cf. UCS 2.2)
- The ESP user wants to create an optimal energy bids and FlexOffers for simultaneous (or else co-optimized) participation in multiple markets to maximize its business profits. (cf. UCS 2.3.)
- The ESP user wants 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 (cf. UCS 2.4)
- Independent large FlexAsset Owner leases storage for several purposes to several market stakeholders (cf. UCS 2.6)

Each one of the five research problems is described in chapters 2-7 below. Depending on the current state of research progress, chapters are structured in the following manner:

- Problem statement, related state-of-the-art and summary of FLEXGRID research contributions
- Proposed system model under study
- Problem formulation including the entire mathematical modeling
- Proposed algorithmic solution
- Simulation setup and performance evaluation results at TRL 3, which demonstrate and prove the concept of FLEXGRID's research innovations.
- Next steps on how to elaborate on the ongoing WP3 research work until M26 in order to test and validate the proposed mathematical models and algorithms with more realistic case studies and the use of real-life datasets.

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

In WP4, we focus on the scientific excellence of the proposed FLEXGRID services at TRL 3. The next goal is to adapt the most important WP4 scientific results in order to be able to serve the business needs of a profit oriented ESP. Hence, in WP6, our focus is on FLEXGRID's research impact on today and future ESP's business.

More specifically, FST's frontend (GUI) - developed by ETRA within WP6 context, will be comprised of the three basic tabs, namely:

- ESP's OPEX minimization
- ESP's CAPEX minimization
- ESP's operating profit maximization

Following up the FST's frontend services, three main algorithms will be implemented in the FST's backend, namely:

- An optimal scheduling algorithm to optimally schedule the observed FlexAssets to reduce OPEX and respond to the issued FlexRequests. The proposed solution is described in chapter 3 (cf. UCS 2.1)
- An optimal siting and sizing algorithm, that produces optimal investment plan to meet desired objective knowing the relevant network topology data. The proposed solution is described in the chapter 4 (cf. UCS 2.2)

- Bi-level algorithm, that co-optimizes ESP's participation in several energy and local flexibility markets to maximize ESP user's profit. The proposed solution is described in chapter 5 (cf. UCS 2.3)

Table 2 below clarifies how the WP4 research results (TRL 3) will be further exploited in WPs 6 and 8.

Table 2: Summary of interactions between WP4 research work (TRL 3) and WP6/WP8 work about potential business impact

FST GUI (WP6)	Mode of operation	Business goal (WP8)
ESP's OPEX minimization	Online	Assume that the DAM dispatch is given and should be respected by the ESP. Then, a FlexRequest issued by DSO/TSO needs to be met by the ESP. Both DAM dispatch and the FlexRequest should be made visible for ESP user. The ESP runs the optimal scheduling algorithm to minimize its OPEX.
	Offline	The ESP user runs various "what-if" simulation scenarios assuming various FlexRequests and FlexAsset portfolios to analyze how different schedules may affect overall profits.
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 bids and FlexOffers to submit in ATP. The FlexOffers (i.e. quantity offered vs. time for a given price assumed) should also be made visible for the FMO user and DSO user.
	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. Only ESP user will be able to visualize the results.

Within FLEXGRID project's context, we follow the NODES flexibility market paradigm and platform setup. Regarding technical and S/W development issues, we rely on NODES real-life business experience, while NPC supports with its consultancy services regarding the integration of the proposed flexibility marketplace in the existing EU markets and regulations. We assume an online flexibility marketplace (i.e. FLEXGRID ATP), in which the profit-oriented ESP acts as a flexibility provider (i.e. FlexSupply side). We also consider that the ESP is an independent market entity and may have contractual arrangements with various FlexAssets. The ESP can use a set of intelligent mathematical models and algorithms to generate optimal business strategies, including bidding, scheduling, siting and sizing. This is exactly where FLEXGRID intelligence comes into the picture. The ESP user will use the frontend and backend services of FLEXGRID's FlexSupplier's Toolkit (FST). In the FST frontend, the ESP user will be able to configure several input parameters and exhaustively run simulation scenarios in an online and offline mode as well as visualize the results via a user-friendly GUI. In the FST backend, respective FLEXGRID WP4 algorithms will run. Part of this FLEXGRID intelligence (at TRL 5) will be open source, so that today and future ESP's business can easily reuse it and potentially extend it.

2 ESP exploits FLEXGRID's advanced forecasting services to predict market prices and FlexAssets' state and curves in the future

2.1 PV Generation Forecasting

2.1.1 Problem statement related state-of-the-art and FLEXGRID research contributions.

Within the previous deliverable D4.1[3], an extensive survey work and literature review were conducted on the related state-of-the-art research that has taken place during the last years in the field of Renewable Energy Sources (RES) generation forecasting and more specifically on Photovoltaic (PV) generation forecasting.

Summarizing this international literature review, 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. The PV generation forecasting can benefit the plant operators with an accurate forecast that can minimize the adverse power quality impacts that are posed by the high shares of distributed PV systems that increase the generation capacity and lead to grid instability. Furthermore, PV generation forecasting can support utilities and plant operators in energy management and dispatchability planning.

The innovative FLEXGRID's research contribution services will include 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, the FLEXGRID's PV generation forecasting services will be located in the Automated Flexibility Aggregation Toolkit (AFAT) and FlexSupplier's Toolkit (FST). Following up the modular-by-design FLEXGRID architecture, the advanced forecasting algorithms will be run in the forecasting engine, while well-designed web APIs will provide: i) the input parameters and data for the execution of algorithms, and ii) the output parameters, which will be sent to the FLEXGRID ATP and then visualized by the ESP/aggregator users.

Summarizing FLEXGRID's scientific contributions, a methodology for both day-ahead and intra-day PV generation forecast were proposed. A Machine Learning (ML) model based on Artificial Neural Network (ANN) will be used. For this approach measured PV outputs, PV system characteristics and weather data will be needed as the main scope is the provision of an accurate forecasting output that can assist utilities and plant operators in the direction of energy management and dispatch planning.

[3] https://flexgrid-project.eu/assets/deliverables/FLEXGRID_D4.1_final_version_30092020.pdf

2.1.2 System model

Within FLEXGRID project's context, ESP and aggregator actors will be provided with advanced forecasting services. These advanced forecasting services will include the ESP and aggregator users generation, by aggregating its end-users generation and also considering the other available assets such as battery storage.

Moreover, ESPs/aggregators want to use the abovementioned forecasting service to increase their profit by making informed market decisions and minimizing the error and deviation from a declared position. The ESPs/aggregators using the forecasting tool will be able to provide accurate energy forecasts that will allow them to dispatch accurately the next steps in an optimal way (both day-ahead and intra-day).

2.1.3 Problem Formulation

Within the previous deliverable D4.1, 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 is optimized according to the input and output parameters. For accurate short-term and medium-term forecasting, three phases are followed, namely:

i. Training: For the training phase of the day-ahead PV generation forecast, actual historical data of the reference systems are used (P_{DC}). Furthermore, on the training phase, Numerical Weather Predictions (NWPs) data were employed in order to evaluate the actual forecasting performance of the developed methodology. The NWP data were derived using a 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.

ii. Validation: During this phase, the hyperparameters of the ML models are being optimized, through a series of statistical and empirical approaches. The optimization phase is stopped when the hyperparameters were not exhibiting any further improvements (in some cases declination is demonstrated).

iii. Testing: During the testing phase, the prediction accuracy performance of the ML model is assessed.

Figure 1 demonstrates the aforementioned procedure.

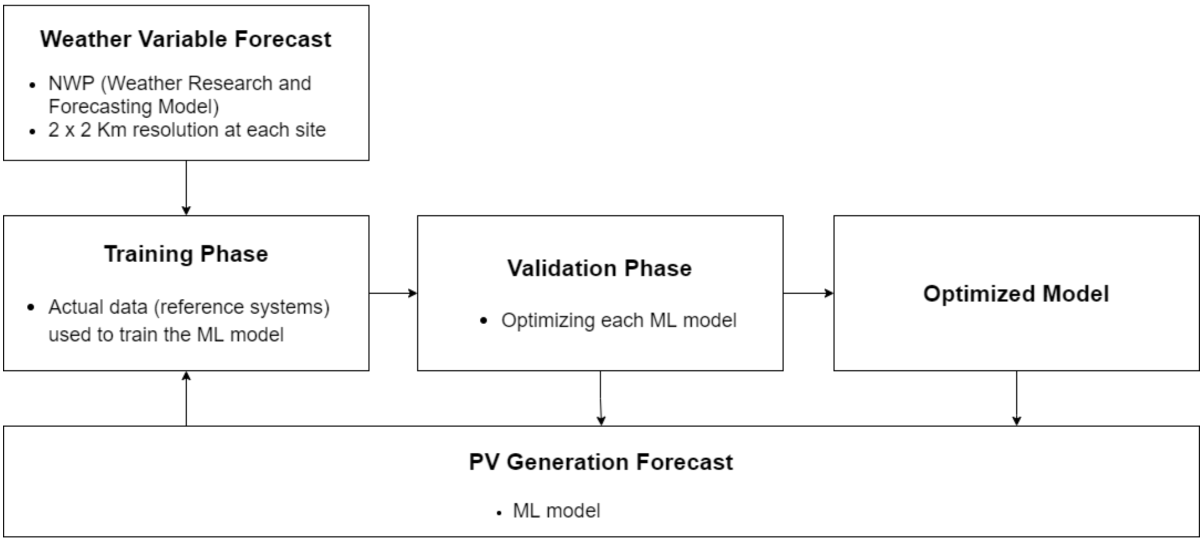


Figure 1: Flow chart of the day-ahead PV generation forecasting model: Overview

2.1.3.1 Artificial Neural Network (ANN)

The ANN model is principally a Bayesian Regularization Neural Network (BRNN) in which a Bayesian Regularization and Back Propagation (BP) algorithm are applied during the training and validation phase. The applied function is given by [1] :

$$y_i = g(x_i) + e_i = \sum_{k=1}^{9} w_k g_k \left(b_k + \sum_{j=1}^{p} x_{ij}\beta_j^{[k]} + e_i\right), i = 1, \ldots, n \tag{1}$$

where e_i is the $N(0, \sigma^2 e)$, s is the number of neurons, w_k is the weight of the k-th neuron, $k = 1, \ldots, s$, b_k is a bias for the k-th neuron, $k = 1, \ldots, s$, $\beta_j^{[k]}$ is the weight of the j-th input to the net, $j = 1, \ldots, p$ *and* $g_k(x)$ is the activation function, in this implementation [1]:

$$g_k(x) = \frac{e^{2x} - 1}{e^{2x} + 1} \tag{2}$$

The function will minimize according to [1]:

$$F = \beta E_D + aE_W \tag{3}$$

where $E_D = \sum_{i=1}^{n}(y_{1,i} - y_{2,i})^2$ is the sum squares error, E_W is the sum of squares of network parameters (weights and biases), $\beta = \frac{1}{2\sigma_e^2}$ and $\alpha = \frac{1}{2\sigma_\theta^2}$, σ_θ^2 is a dispersion parameter for weights and biases. The regularization term applied was the squared sum of the weights of the neural network given by [1]:

$$\varepsilon_T = \beta\varepsilon_D + \alpha\varepsilon_R = \frac{\beta}{2}\sum_{k=1}^{N}(y_k - t_k) + \frac{\alpha}{2}\sum_{i=2}^{M} w_i \tag{4}$$

where *α* and *β* are coefficients assigned to each term. The second term in Eq. 4 is called weight decay, as it ensures that the weights of the network do not exceed the total error of the network.

The density function of the weights, of the hidden layer, was updated according to Bayes' rule [1]:

$$P(w\,|D,\ \alpha,\ \beta,\ M) = \frac{P(D\,|w,\ \beta,\ M)\,P(w\,|\alpha,\ M)}{P(D\,|\alpha,\ \beta,\ M)} \quad (5)$$

where D represents the dataset, M the model used for the neural network and w is the vector of the neural network's weights. $P(w|\alpha, M)$ represents the values of weights prior to the dataset input. $P(D|w,\beta, M)$ is the probability of the data occurring based on the weights and $P(D|\alpha,\beta, M)$ is a normalization factor , which ensures that the total summation of the probability is one.

2.1.3.2 Data processing and quality verification methodology

The detection of invalid and incorrect data is quite important for the accuracy of the PV generation forecasting ML model as the training phase is based on the historical data of the reference systems. The quality of the actual historical datasets of the utility-scale PV systems must be analyzed in order to verify the usage of the plants as reference systems for upscaling to larger aggregation areas.

Data integrity is crucial for the performance and reliability analysis of PV systems since actual measurements commonly exhibit invalid data caused by outages and component failures. PV data processing and quality verification methodology developed to ensure improved PV performance and reliability analyses. Data Quality Routines (DQRs) were developed to ensure data fidelity by detecting and reconstructing invalid data through a sequence of filtering stages and inference techniques.

The data processing and quality verification methodology is based on the quantifiable criteria from IEC 61724 [2]–[4] standard and other PV data quality reports [5]. It is a methodology of sequentially structured DQRs that includes the application of initial statistics, consistency examination, filtering, detection of invalid values and data rates and treatment of invalid data (See Figure 2).

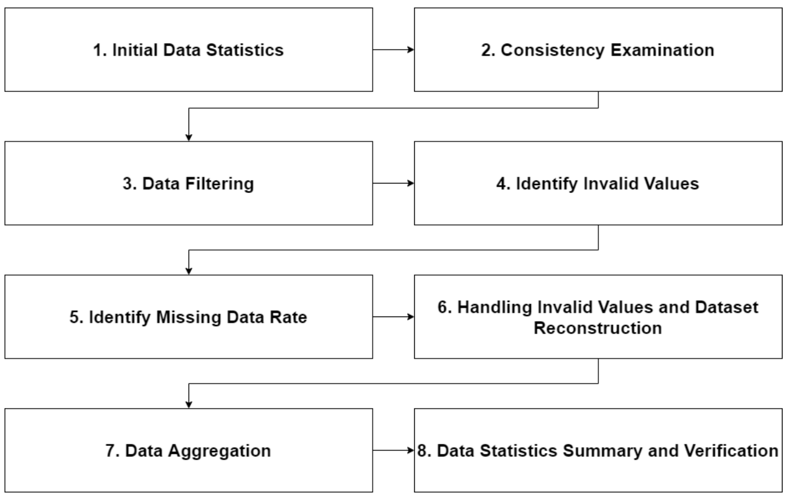


Figure 2: Flowchart of data processing and quality verification methodology

2.1.4 Algorithmic solution

2.1.4.1 Bayesian Regularization Neural Network (BRNN)

Summarizing the previous deliverable D4.1, for the number of identified reference PV systems, ML techniques and more specifically ANNs were applied to implement the PV forecasting generation model. In order to yield the day-ahead forecast, the model was subsequently fed with the NWPs.

Moreover, a Bayesian Regularized ANN (BRNN) was utilized (See 2.1.3.1). The BRNN model is a simple Multi-Layer Perceptron (MLP) ANN, in which a Bayesian regularization has been applied to its training phase. A day-ahead PV production forecasting accuracy comparison of different ML predictive models showed that the BRNN model scored the highest forecasting accuracy [6].

2.1.4.2 Upscaling and Aggregation Methodology

In order to yield day-ahead and hour-ahead PV generation forecasts for a larger capacity aggregated balancing area, an upscaling method is proposed. For the upscaling method statistical information of all PV systems placed in the aggregation area are needed.

The required parameters for the implementation of the upscaling process are the nominal power and the location of the individual PV systems. Figure 3 demonstrates the procedure followed to develop the aggregated day-ahead and hour-ahead forecasts.

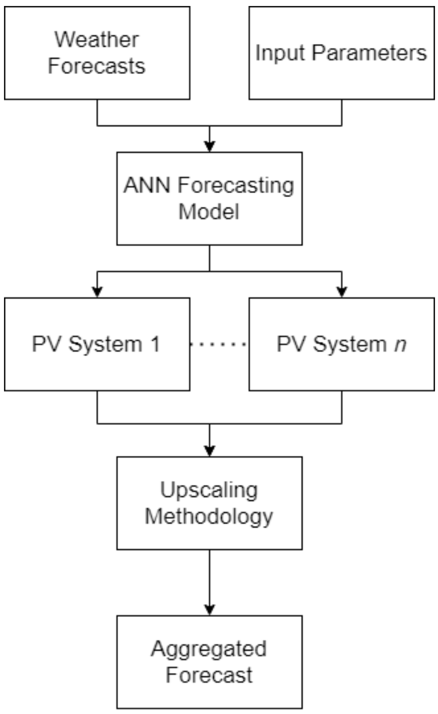


Figure 3: Flowchart of PV generation aggregation forecasts algorithm

2.1.5 Simulation setup and performance evaluation results

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_s, 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):

$$MAE = \frac{1}{n} \cdot \sum_{i=1}^{n} \left| y_{observed,i} - y_{forecasted,i} \right| \quad (6)$$

The mean absolute percentage error (MAPE) which is given by:

$$MAPE = \frac{100}{n} \cdot \sum_{i=1}^{n} \left| \frac{y_{observed,i} - y_{forecasted,i}}{y_{actual,i}} \right| \quad (7)$$

The root mean square error (RMSE) which is given by:

$$RMSE = \sqrt{\frac{1}{n} \cdot \sum_{i=1}^{n} (y_{observed,i} - y_{forecasted,i})^2} \quad (8)$$

The normalized root mean square error (nRMSE) which is given by:

$$nRMSE = \frac{100}{P_{nominal}} \sqrt{\frac{1}{n} \cdot \sum_{i=1}^{n} (y_{observed,i} - y_{forecasted,i})^2} \quad (9)$$

where $y_{actual,i}$ and $y_{predicted,i}$, is the actual and predicted power respectively, $P_{nominal}$ is the peak power of the PV system for the production.

2.1.5.1 Data processing and quality verification methodology simulation results

To determine the importance of the data processing and quality verification in terms of performance accuracy of the forecasting model, some simulations were made.

For the respective simulations, a test set period of 200 days on hourly intervals were used. Figure 4 shows the forecasting accuracy performance of the ANN model, evaluated by employing the daily nRMSE over a test set period of 200days. In Figure 4, a comparison between the ANN forecasting model without 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 $< 100W/m^2$ 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 4, a 2% decrease in the average nRMSE was noticed after correction of the input data.

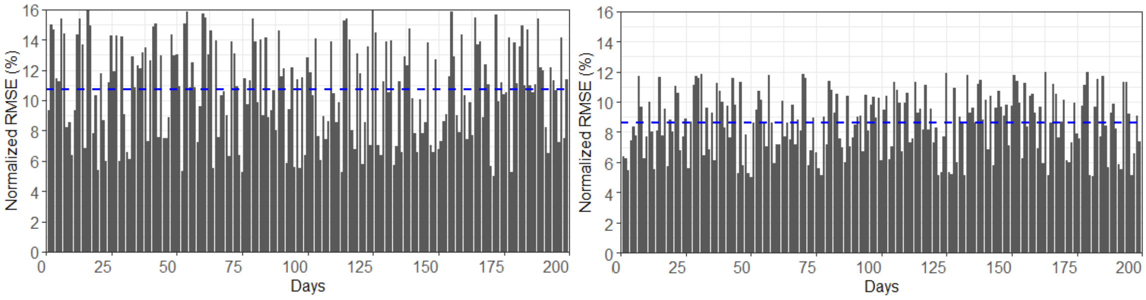


Figure 4: Daily nRMSE of: (a) Forecasting model without DQRs and (b) Forecasting model with DQRs. The blue dashed line of both figures demonstrates the average nRMSE.

2.1.6 Next steps

Within the M19-M26, priority will be given to the completion of the PV generation forecasting simulations and then, a comparison of the forecasted and real PV data will follow. These simulations will not only be tested with historical PV data-frames of parks located in Cyprus but also with historical PV data-frames of parks that are located in different climates. This will present how accurate is the output of the ML forecasting algorithm.

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 Problem Statement related state-of-the-art and FLEXGRID research contributions

Market price forecasting is a part of the HLUC04_UCS04 that deals with the forecasting services that will be provided to the ESP and aggregator users. More specifically, a market price forecasting tool will be developed in view of facilitating the optimal FlexOffer process towards efficient ESP/aggregator participation in all types of distribution level flexibility markets and wholesale/balancing markets (i.e. transmission system level).

In deliverable D4.1, a detailed literature review on both the nature of electricity markets, involving their operation framework and regulatory context, and on the methods/ mathematical models developed for short-term electricity price forecasts was conducted.

The literature survey showed that many mathematical models have been developed for short-term electricity price forecasts, mainly for the Day-Ahead market, because it is the more active market in terms of number of players. The main algorithms developed out of these mathematical models were aimed to achieve best possible forecasting accuracy of the next day prices.

The basic mathematical element of the proposed methodology is the Extreme Learning Machine (ELM). It is a simple and computationally efficient mathematical method, and in combination with other statistical procedures can give forecasts of accuracy that is in line with the objectives of the FLEXGRID. Given the complex nature of market price forecasting, as it involves many inter-related and confounding variables and parameters, ELM could easily be combined with other methods to improve both the prediction of actual hourly rates and probably identify the appearance of unexpected extremely high or negative prices.

The developed forecast tools is expected to facilitate the integration of more RES in electricity grids as their owners will be able to plan better their service and optimize their profits. In addition, the availability of forecasts could enable risk assessments that in turn could provide insights to ESP's planning and management of their flexibility assets. Moreover, the ESPs can use the market forecasts to efficiently enable their participation in various distribution-level flexibility markets (DLFMs) and existing wholesale markets. A final objective is to further improve the forecast and Market Forecast Accuracy Levels (MFAL).

2.2.2 System model

The market price forecasting algorithm belongs to the FLEXGRID's forecasting engine which will reside in the Automated Flexibility Aggregation Toolkit-AFAT (Figure 5) and FlexSupplier's Toolkit-FST (Figure 6). It will be available for use by both aggregator and ESP market stakeholders. Based on the modular-by-design architecture, the market price forecasting will run in the forecasting engine. APIs (Figure 7) i) will be providing to the forecasting tool the input parameters and ii) will be transferring the generated forecasts to FLEXGRID ATP to be exploited by ESP/Aggregator. In addition, this algorithm will exploit historical data from any auction-based market with uniform pricing.

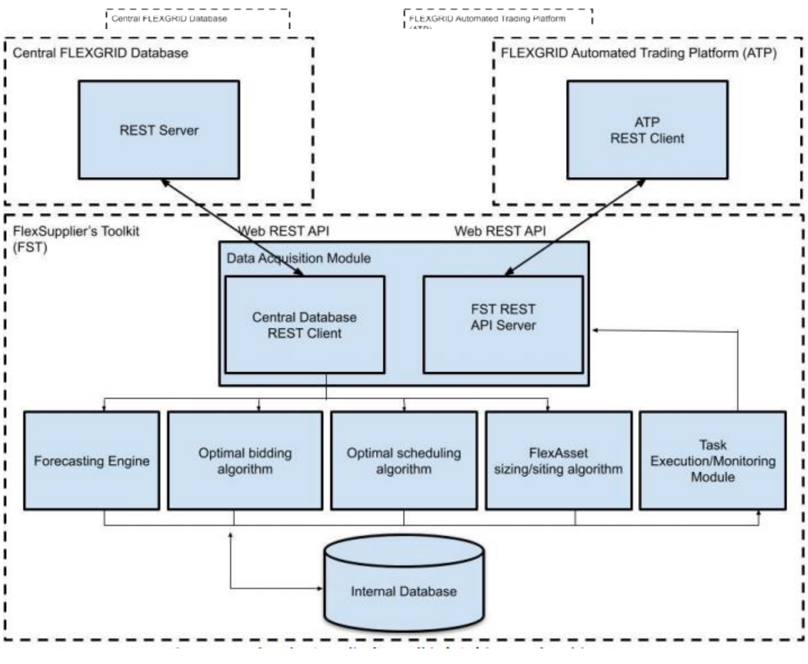


Figure 5: The FlexSupplier's Toolkit (FST) internal architecture

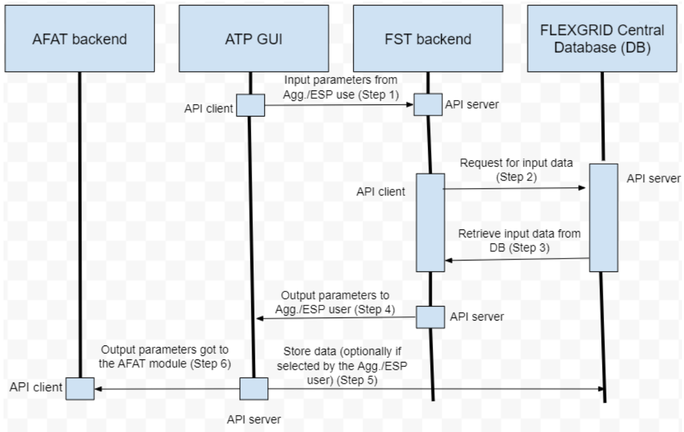


Figure 6: API sequence diagram with details about all the message exchanges between the involved FLEXGRID S/W components

The regulatory context followed is that of Nord Pool's Day-Ahead market. In the Day-Ahead market, participants submit 24 bids/offers for each hour of the next day (Figure 8) and thereby the electricity delivery contracts are hourly.

Figure 7: Market decision timeline: one Day-Ahead market

Trading in the Nord Pool market takes place through auction and the trading hours are the subsequent 24 hours starting at 00:00 CET. The gate closes at 12:00 CET and at 12:43 CET the results are announced. Also, for each bid, the quantity and the price for which the participants are willing to buy/sell must be defined [7]. After closing the gate, all offers for each hour are collected and the buy and sell curves are formed (Figure 9). Buy curves are formed in descending order, while sales curves are formed in ascending order. The intersection of these two curves gives the market equilibrium. This price is the same (uniform price) for all participants. That is, offers for sale that are not higher than the equilibrium price are accepted. On the contrary, offers for purchase that are higher than the equilibrium price are accepted.

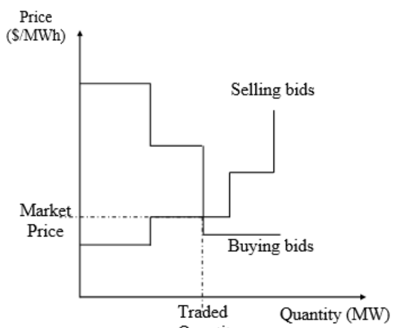


Figure 8: Spot Price and traded quantity for a given hour h

2.2.3 Problem Formulation

2.2.3.1 Extreme Learning Machine

An ELM is a neural network with a single hidden layer of L neurons is shown in figure 10.

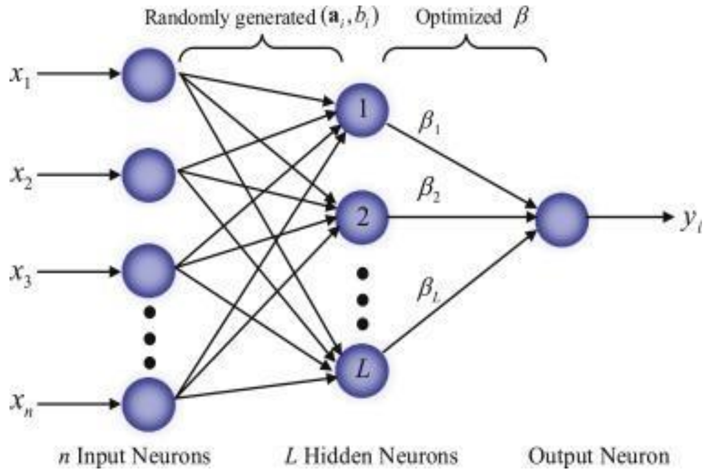


Figure 9: A typical structure of ELM

Given that its activation function is $g(x)$ it learns to model N arbitrary data samples (x_i, y_i) , $x_i \in R^n$ using the following equation:

$$\sum_{i=1}^{L} g_i(x_i)\beta_i = \sum_{i=1}^{L} g\left(w_i \cdot x_j + b_i\right) = y_j \tag{10}$$

where w_i is the weight vector connecting the i_{th} hidden neuron to the n input neurons, β_i is the weight vector connecting the i_{th} hidden neuron with the output neuron. The bias of each hidden neuron is denoted by b_i [8]
The usually used activation function is the sigmoid function that takes values between (0-1) and is given by:

$$g(x) = \frac{1}{1 + e^{-x}} \tag{11}$$

Rewriting equation (10) as:

$$H\beta = Y \tag{12}$$

where *H* is the so-called hidden layer matrix given by

$$\boldsymbol{H} = \begin{pmatrix} \boldsymbol{g(w_1, b_1, x_1)} & \cdots & \boldsymbol{g(w_L, b_L, x_1)} \\ \vdots & \ddots & \vdots \\ \boldsymbol{g(w_1, b_1, x_n)} & \cdots & \boldsymbol{g(w_L, b_L, x_n)} \end{pmatrix}_{\boldsymbol{n \times L}} \tag{13}$$

and β and Y are corresponding vectors of the weights connecting the hidden neurons with the output and of the training (or testing) target values, given by [8] :

$$\boldsymbol{\beta} = \begin{bmatrix} \boldsymbol{\beta}_1^T \\ \vdots \\ \boldsymbol{\beta}_L^T \end{bmatrix}_{L\times m} \qquad \boldsymbol{Y} = \begin{bmatrix} \boldsymbol{y}_1^T \\ \vdots \\ \boldsymbol{y}_N^T \end{bmatrix}_{N\times m} \tag{14}$$

The output weight vector β can be calculated by solving the following equation:

$$\boldsymbol{\beta} = \boldsymbol{H'Y} \tag{15}$$

where *H'* is the Moore-Penrose generalized inverse or pseudoinverse of the matrix *H*.

2.2.4 Algorithmic solution

Historical prices for three days are used first to train the network, that is to compute the vector β, using randomly selected weights (*w*) and biases, b Then, the historical prices are multiplied by the random input weights (*w*) and the multiplication result is added to the biases. After this the result enters in the activation function and thus the output of the Hidden Layer (*H*) occurs. Then, the inverse (or Moore-Penrose pseudoinverse) of the Hidden Layer is calculated and its result is multiplied by the 24 historical prices (or Data *Y*). This is how output weights (β) emerges, which will give the forecasts for the Day-Ahead prices.

In addition, the ELM is applied per hour. That is, for each hour a different input weight (W) is used for multiplication and a different bias for addition. Then, a different output of the Hidden Layer (H) occurs for each hour and a different inverse is applied for each hour.

As mentioned above, sigmoid function is commonly used as the activation function. But we used other functions to see if it gives better results. The other functions we used together with the results are shown in Table 2.

2.2.5 Simulation setup and performance evaluation results

The data we use come from the Nord Pool's website (they are publicly available), and they are hourly prices [9]. Figure 11 shows a sample of hourly electricity prices $\left(\frac{€}{MWh}\right)$

The scenario we implement is the following: The algorithm will have prices as its input from three consecutive days (or 72 hourly prices) and will output the 24 hourly prices of the fourth day (cf. Figure 12 below).

Time	Prices
00:00:00	24,7
01:00:00	24,1
02:00:00	23,9
03:00:00	24
04:00:00	24,6
05:00:00	25,8
06:00:00	28,2
07:00:00	30,9
08:00:00	49,2
09:00:00	50
10:00:00	55,4
11:00:00	56,5
12:00:00	52,1
13:00:00	56,5
14:00:00	58
15:00:00	57,6
16:00:00	60,1
17:00:00	65,2
18:00:00	59,6
19:00:00	41,5
20:00:00	37,7
21:00:00	34,8
22:00:00	31
23:00:00	27,4

Figure 10: Sample of electricity hourly prices

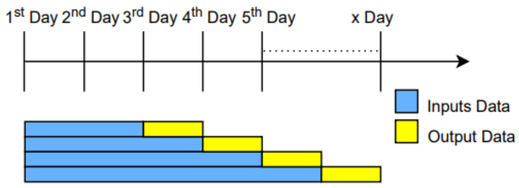


Figure 11: Algorithm input and output data diagram

The KPI is the Mean Absolute Error (MAE) eq. (6). For example, 4,5 means on average there will be a difference of 4,5 $\left(\frac{€}{MWh}\right)$ between the actual and the forecast value. Since this is the absolute error the difference does not indicate over-forecasted or under-forecasted value.

Table 3 shows the results obtained using different activation functions.

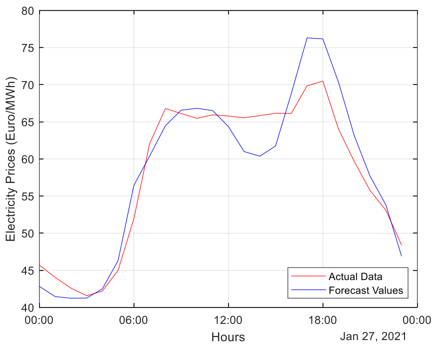
Table 3: Results obtained using different activation functions (the bold values are the best results for each case)

Activation Functions	Functions $f(x)$	Forecast Days						
		27/1	28/1	29/1	30/1	31/1	1/2	1/1
		MAE=$\frac{1}{n}\sum_{i=1}^{n}\left\|y_{observed,i} - y_{forecasted,i}\right\|$						
Sigmoid	$\frac{1}{1+e^{-0.0010x}}$	2,97	3,77	6,42	9,83	6,84	35,60	10,85
Deriv. Sigmoid	$f(x)(1-f(x))$	6,48	3,50	3,92	9,29	7,71	34,07	11,34

tanh	$\frac{e^{0.0010x} - e^{-0.0}}{e^{0.0010x} + e^{0.0}}$	3,15	3,56	5,88	9,64	7,03	35,07	10,98
Deriv. tanh	$1 - f(x)^2$	6,25	3,37	4,05	9,32	7,35	34,18	11,28
arctan	$0.0010x$	2,90	5,50	8,09	10,11	6,61	36,41	10,58
Deriv. arctan	$\frac{1}{(10^{-5}x^2) + 1}$	6,24	3,37	4,05	9,32	7,35	34,18	11,28
EliotSig	$\frac{x}{1 + \lvert 0.0010x \rvert}$	2,65	4,92	7,59	10,05	6,64	36,21	10,63
Deriv. EliotSig	$\frac{1}{(1 + \lvert 0.0010x \rvert}$	10,20	6,53	2,10	8,77	8,32	32,59	12,15

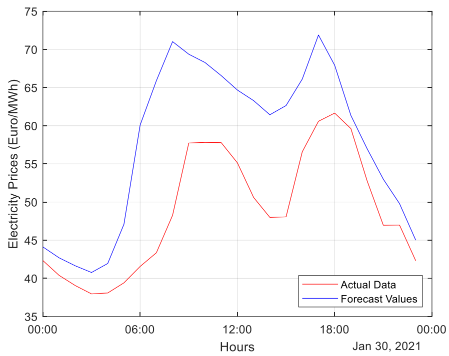
Note that the co-efficients in the equations of the activation functions were placed because the result is even better. Moreover, other co-efficients were tested but did not give better results.

The curves in the graphs of Figure 13 depict the forecast prices obtained by the algorithm and the actual prices. The forecast prices shown are those corresponding to the activation function that yielded the best MAE.



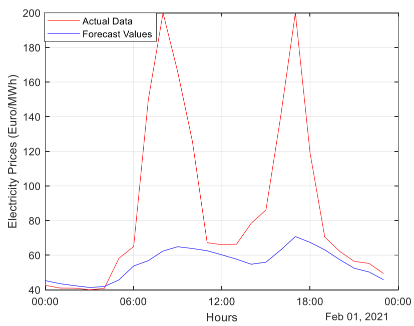
MAE:

2,65



MAE:

8,77



MAE:

32,59

Figure 12: Forecast and actual prices for January 27, 30 and February 01 of the year 2021

It can be concluded from Table 3 and Figure 13 that the algorithm for some days gives very good results. On the contrary, there are days (e.g. 1/2), where the results exhibit high MAE. The main reason for this is the presence of extremely high values ("outliers"). It is discussed in the "Next Steps" section that the integration of exogenous factors such as consumption, production and weather conditions may enable the prediction of such events.

2.2.6 Next Steps

Regarding the next steps, as shown by the results obtained so far, the algorithm cannot predict the "outliers" (extreme high prices or negative prices). So, we will turn our attention in this direction. The inclusion of exogenous factors or the incorporation of another method that will be associated with extreme prices will solve this problem.

In response to the above, a preliminary analysis is depicted in Table 4. In this table, the number of negative prices that occurred for the years 2015-2020 and the yearly price standard deviation of each market in the Nord Pool database [9] are shown. In overall, it can be seen that the number of negative price events increased in 2020, and one is tempted to somehow attribute this increase to Covid-19 crisis.

In addition, the yearly standard deviation of prices in 2020 was higher in many countries compared to 2019, indicating higher volatility. Norway is an exception to this and the reason is that it has a more homogeneous electricity system, which results in prices not being so volatile.

Table 4: Statistical analysis of European day-ahead electricity markets

Country	Zones (Names)		Years					
			2015	2016	2017	2018	2019	2020
Denmark	West Denmark	Num. of negative prices	65	62	75	48	116	162
		Yearly Standard Deviation of Prices $\left(€/_{MWh}\right)$	11,12	9,76	10,66	15,06	13,15	17,43
	East Denmark	Num. of negative prices	36	49	57	40	86	71
		Yearly Standard Deviation of Prices $\left(€/_{MWh}\right)$	11,47	13,28	10,97	16,72	12,66	19,72
Estonia	-	Num. of negative prices	-	-	-	-	-	5
		Yearly Standard Deviation of Prices $\left(€/_{MWh}\right)$	14,38	12,81	9,54	15,28	15,82	21,44
Finland	-	Num. of negative prices	-	-	-	-	-	9
		Yearly Standard Deviation of Prices $\left(€/_{MWh}\right)$	14,46	13,14	9,61	15,12	15,29	21,11
Germany	-	Num of negative prices	Not available data				178	298

		Yearly Standard Deviation of Prices $\left(\text{€}/_{MWh}\right)$					15,52	17,50
Norway	Oslo	Num. of negative prices	-	-	-	-	-	5
		Yearly Standard Deviation of Prices $\left(\text{€}/_{MWh}\right)$	7,83	10,20	4,88	10,47	8,34	8,28
	Kristiansand	Num. of negative prices	-	-	-	-	-	5
		Yearly Standard Deviation of Prices $\left(\text{€}/_{MWh}\right)$	7,65	6,57	4,63	9,38	8,23	8,26
	Bergen	Num. of negative prices	-	-	-	-	-	1
		Yearly Standard Deviation of Prices $\left(\text{€}/_{MWh}\right)$	7,68	6,90	4,54	9,48	8,27	7,91
	Molde	Num. of negative prices	-	-	-	-	-	-
		Yearly Standard Deviation of Prices $\left(\text{€}/_{MWh}\right)$	7,77	10,47	5,54	10,41	7,87	6,92
	Trondheim	Num. of negative prices	-	-	-	-	-	-
		Yearly Standard Deviation of Prices $\left(\text{€}/_{MWh}\right)$	7,77	10,47	5,54	10,41	7,87	6,92
	Tromso	Num. of negative prices	-	-	-	-	-	-
		Yearly Standard Deviation of Prices $\left(\text{€}/_{MWh}\right)$	7,35	7,88	5,24	9,53	7,57	6,48
Latvia	-	Num. of negative prices	-	-	-	-	-	5
		Yearly Standard Deviation of Prices $\left(\text{€}/_{MWh}\right)$	18,05	16,40	10,35	16,92	15,82	20,88
Lithuania	-	Num of negative prices	-	-	-	-	-	5

		Yearly Standard Deviation of Prices $\left(€/_{MWh}\right)$	18,12	16,89	10,81	17,14	15,82	20,91
Sweden	Lulea	Num. of negative prices	-	-	-	-	-	9
		Yearly Standard Deviation of Prices $\left(€/_{MWh}\right)$	8,19	11,74	7,16	11,56	9,89	11,51
	Sundsvall	Num. of negative prices	-	-	-	-	-	9
		Yearly Standard Deviation of Prices $\left(€/_{MWh}\right)$	8,21	11,74	7,16	11,56	9,89	11,51
	Stockholm	Num. of negative prices	-	-	-	-	-	9
		Yearly Standard Deviation of Prices $\left(€/_{MWh}\right)$	9,73	12,33	7,97	12,06	10,38	19,29
	Malmo	Num. of negative prices	-	-	-	-	-	10
		Yearly Standard Deviation of Prices $\left(€/_{MWh}\right)$	10,61	12,52	8,95	14,23	11,30	20,20

3 ESP's OPEX minimization problem

The focus in this chapter is on the research problem of the UCS 2.1. In the center of the problem, we observe actions from an Energy Service Provider (ESP). 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 on energy and capacity wholesale markets, sell the energy on the retail market and take part in near-real-time flexibility markets [D2.1][4]. 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, and
- Near-real-time Balancing Market (BM) operated by the TSO

Within WP4 context, we develop the mathematical model, the algorithm and conduct system-level simulations at TRL 3. Our ultimate goal is to integrate the UCS 2.1 algorithm in the FLEXGRID ATP (TRL 5) and more specifically in the FlexSuppliers' Toolkit (FST) following a similar methodology like UCS 2.2 and 2.3 algorithms.

In the FST module of the FLEXGRID ATP, the ESP user will be able to run the optimal scheduling algorithm in two operating modes. In the online operation, the ESP user will have the initiative. According to the market price forecasting for 3 markets (i.e. day-ahead, DLFM, balancing) and the day-ahead schedule, a new optimal schedule is calculated taking in consideration potential benefits of participating in DLFM and needed balancing in the BM. In the offline operation mode, the ESP user will be able to run various "what-if" simulation scenarios via running the optimal scheduling algorithm for OPEX minimization efforts to investigate what can be achieved in various scenarios.

3.1 Problem statement, related state-of-the-art and FLEXGRID research contributions

The world, and especially countries in the European Union are in a tremendous process of energy transition [10]. Electricity generation based on fossil fuels is continuously replaced by Renewable Energy Sources (RES) that are characterized by variable and unpredictable generation. This for consequence may result in various problems for the network operators. From line and transformer congestion, voltage limit violation to difficulties in securing enough generation to cover the demand thus creating a need for some kind of flexibility services.

In addition to the proliferation of distributed, unforeseeable RES, the market structure is also evolving. The whole electricity market structure is in the process of liberalization and

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

deregulation, oriented towards open market paradigm. Vertically integrated structure is unbundled separating regulated activities (e.g. transmission) from the unregulated (e.g. generation and distribution companies). Moreover, end-users are incentivized to become active users (*prosumers*) in order to offer flexibility services to the system operator when needed in exchange for some reimbursement. Having in mind EU countries, one of the greatest legislative accelerators is the *Clean Energy for all Europeans Package* [11].

Profit-oriented companies such as ESPs in that manner have (or will have) the opportunity to participate in various markets and to offer a wide variety of services such as flexibility services to the system operators which are in charge of ensuring secure and reliable energy transmission having in mind intermittent RES nature. This creates space for making diverse business strategies. Although ESP may generate high profits, suboptimal strategies can drastically reduce it and even endanger its market position. Hence, OPEX minimization problem based on optimal scheduling 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.

Within FLEXGRID project's context, the Distribution Level Flexibility Market (DLFM) is proposed to address the aforementioned issues caused by the high RES penetration. Such market may encourage further investments in DERs and their market participation.

Existence of DLFM creates on the one hand opportunities for TSO and DSO to procure flexibility services to avoid network problems and secure reliable energy transmission, while on the other hand it presents an opportunity for profit-oriented ESPs to generate more profit by offering its services on the new DLFM. As ESP already takes part in other markets, it is important to generate a schedule that yields greater profit in comparison to the old one (i.e. DA schedule without DLFM), having in mind the imbalance costs that may arise if the schedule is not respected.

In UCS 2.1, we consider a profit-oriented ESP which owns FlexAssets and provides flexibility services in addition to the usual market participation (i.e. wholesale market level).

Although the emphasis of the research problem in UCS 2.1 lies on the development of the optimal scheduling algorithm to minimize OPEX, optimal bidding strategies and precise modelling of the FlexAssets accompanied with the precise forecasting algorithms (market prices, end-user consumption and RES production) have also a big impact on ESP's business strategies. Observing the FLEXGRID project as a whole, other research problems do deal with those topics in great detail, hence the project offers holistic solutions to the interested parties. Nevertheless, a survey on related works, done within FLEXGRID D4.1, included broader picture than purely scheduling problem.

Starting with the means of energy storage systems (ESS), solutions such as batteries are gaining more and more importance, as their price is going down, and slowly becoming integral part of modern networks. In that manner, it is interesting to examine how battery storage units act almost independently on the electricity markets [12]–[17]. But even more useful are articles that explain mutual benefits of systems that combine batteries with RES

[18]–[21] when planning their actions. Many of the observed articles use predictions to enhance their models. The authors in [22] state that they used load and generation power predictions, but the model lacked weather forecasts which could further improve the results. Reference [23] tackled forecast inaccuracies using the rolling horizon concept in which its data is in each time stamp updated from the forecast variable, thus decreasing the negative impact of possible previous forecast mistakes. The authors in [24] developed a 24-hour optimal scheduling algorithm for ESS using load and renewable energy forecasting. They argue that their short-term models are able to maximize customer's profit by energy arbitrage, minimize the peak load to reduce the contract power and minimize the number of charging/discharging cycles to prolong the expected life of ESS. Enhanced battery models that describe battery charging/discharging processes and life cycle in general more accurately would be useful addition to the precise forecasts in battery scheduling process. Not many articles tackle the matter in such detailed manner, but there are articles such as [16] that consider battery characteristics in more detail.

Reference [25] is much closer to the problem observed in this chapter. They have modelled optimal day ahead schedule of the system with high penetration of RES considering DSM. The objective function was to minimize energy cost. Wind speed and solar radiation were treated as uncertain parameters, while Monte Carlo simulation and fast forward selection were used for scenario generation and reduction, respectively. Results have shown that elastic loads may significantly help in reducing overall costs and pollutant emission. The concept of a cooperation (through bi-level programming) between a utility company (ESP in FLEXGRID's case) and end users (residential and industrial) has been very roughly explained in [26]. The ESP's objective is cost minimization, and the end users' objective is to get as much economic compensation as possible for providing demand response services. Speaking of demand response, it is important to mention that it is a widely researched topic. From control mechanisms such as one described in [27], where the aim is (by using two-layer communication), to equalize as much as possible the demanded aggregated load profile with the actually aggregated load profile, to modelling day-ahead based schedule, while considering demand response possibilities [28].

The literature survey conducted in D4.1 proved that academia is really interested and devoted to the topic of FLEXGRID project. Many aspects have been examined, but they differ from the UCS 2.1. The biggest difference lies in the formulation of the new market concept of DLFM that is introduced in FLEXGRID.

To the best of our knowledge, this work uses novel, still not modelled, concept of the optimal scheduling for a Battery Storage Unit (BSU) owner, which is profit oriented market player and has the possibility to participate both in electricity common markets (e.g. day-ahead), but also to provide flexibility services to the respective DSO (e.g. DLFM).
As the most important contributions from the FLEXGRID's UCS 2.1, the following ones may be considered:

- Modeling of the optimal scheduling algorithm including the novel DLFM in addition to the DAM and BM. With clear chronological structure of their clearing times, concerning the current market legislative and structural situation of the existing power markets. In that manner, it is also considered what is the easiest way to incorporate such a market to the existing system arrangement.

- The process of scheduling and rescheduling modelled in such a way that DLFM clearing is in the timeframe between DAM and BM. Considering it as the least intrusive way to integrate DLFM into the current market and regulatory context.
- Emphasis on quality of scenarios (i.e. comprehensiveness of possibilities) and forecast accuracy. To achieve this, models and results developed as part of WP3 (primarily market price and RES production predictions) will be used in addition to the work done in WP4.

3.2 System model

For the research purposes of UCS 2.1, we consider a market architecture that consists of DAM, BM and proposed Distribution-Level Flexibility Market. 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. And this closes the circle of three markets where ESP, in the context of this UCS, is able to participate in (see figure below for the better understanding). It is also important to notice that the model is **not** network-aware, so network constraints are not taken in consideration in any of the three mentioned markets.

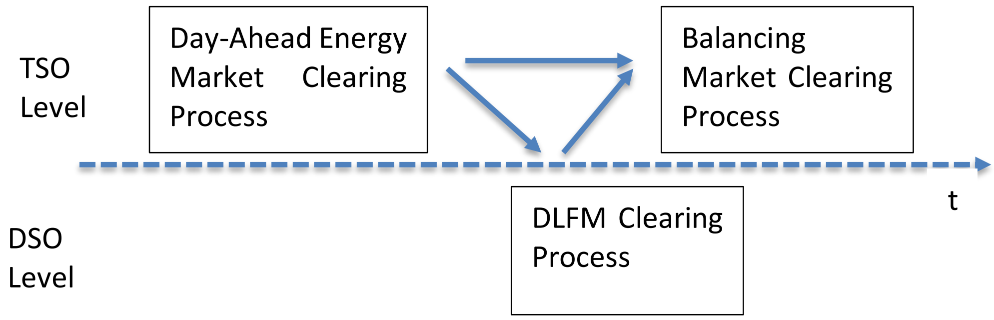


Figure 13: Proposed system model of FLEXGRID UCS 2.1

Figure 15 presents the market setup used for the purposes of UCS 2.1. It consists of three markets, two already existing ones – DAM and BM, and one proposed by the FLEXGRID project – DLFM. Here specifically, we consider the Reactive DLFM (R-DLFM) as it is compatible with the existing EU regulatory framework. In that way, the sequence of the existing markets stays the way it is now and R-DLFM is inserted between the DAM and BM, so no regulatory changes are necessary. This paves the way for the implementation of the UCS 2.1 on the FST module of the FLEXGRID ATP platform in TRL 5. The R-DLFM starts after the DAM clearing process in order to deal with the distribution network (DN)-related problems such as local congestion and voltage control issues and BM serves the respective ESP to balance the altered DA schedule if needed. Dotted red lines indicate the two main points that the optimal scheduling algorithm focuses on. First, it takes as input given DA schedule, then it generates DLFM market offers under consideration of adjustments on the BM.

More technical details about all these issues as well specific performance evaluation results (i.e. sensitivity analysis) for various system-level simulation scenarios shall be demonstrated in following chapters of this deliverable.

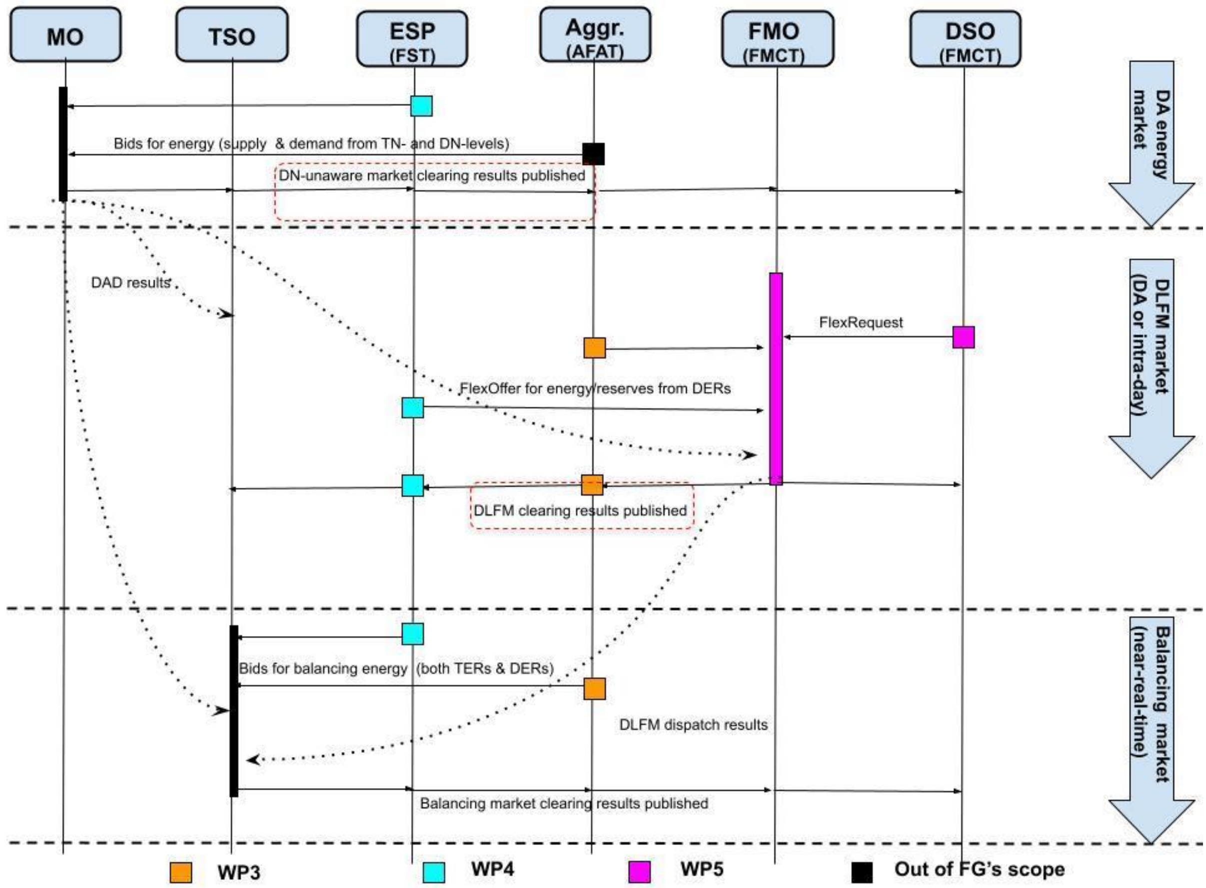


Figure 14: Placement of UCS 2.1 mathematical model and algorithm in the Reactive DLFM architecture proposed by FLEXGRID

3.3 Problem Formulation

UCS 2.1 - ESP's OPEX minimization problem is a single-level optimization problem. Most generally speaking, the emphasis lies on the scenario quality and modelling of the energy storage units and demand response. Moreover, the focus is on the optimal scheduling algorithm, while other research efforts in WP4 and FLEXGRID project as whole, address other related issues such as optimal sizing/siting (cf. UCS 2.2), optimal bidding (cf. UCS 2.3 & 2.4), etc. To model the process investigated in the scope of this UCS, two optimization problems are formulated consequently. The first one (baseline problem) does not consider the R-DLFM, but only DAM. So, it is optimization of the ESP's market participation under the existing conditions. More precisely, the result of this problem is the DA schedule. The second one (DLFM problem) takes the DA schedule as an input parameter and then runs optimization now having possibility to participate in the DLFM, but also keeping in mind that any deviations of the DA schedule are to be penalized in the BM.

3.3.1 Baseline problem – Business as Usual (BaU)

In the BaU problem, the goal is to get the day-ahead schedule concerning the respective profit-maximizing ESP. The ESP's goal is to participate with such strategy that maximizes overall profit in the observed time period (one day). The baseline formulation of the first problem is given below in the equations: (1)-(8)

$$Max \sum_{t=1}^{24} DA_t \cdot \left(p_t^{dch} - p_t^{ch}\right) \cdot \Delta t^h \ (1)$$

subject to

$$soe_t = soe_{t-1} - p^{dch} \cdot \Delta t^h + \ p_t^{ch} \cdot \eta^E \cdot \Delta t^h, \qquad \forall t \in T \ (2)$$

$$p_t^{ch} \leq \frac{CHAR^{max}}{\eta^E} \cdot ch_t^{bin}, \qquad \forall t \in T \ \ (3)$$

$$p_t^{dch} \leq DISCH^{max} \cdot dch_t^{bin}, \qquad \forall t \in T \ (4)$$

$$ch_t^{bin} + dch_t^{bin} \ \leq 1, \qquad \forall t \in T \ (5)$$

$$soe_{24} \geq SOE_0, \qquad (6)$$

$$soe_t \leq C^E, \qquad \forall t \in T \ (7)$$

$$p_t^{ch}, p_t^{dch}, soe_t, ch_t^{bin}, dch_t^{bin} \geq 0, \qquad \forall t \in T \ (8)$$

$$ch_t^{bin}, dch_t^{bin} \ \in \{0,1\}, \qquad \forall t \in T \ (9)$$

The objective function (1) maximizes price-taker ESP's profit from the participation on the DA market. It is assumed, that all bids are accepted. To ensure such a strong assumption, ESP bids a very low price so the bid would always be accepted. Parameter *DA* represents hourly electricity prices, while variables p^{dch} and p^{ch} denote discharging and charging power, respectively. Parameter Δt^h *represents* the duration of the observed time intervals (i.e. one hour) and multiplies (disch)charging power variable(s) to express energy. Constraint (2) indicates battery's state of energy (variable: *soe*) in regard to the charging and discharging process in a efficiency aware manner (full-cycle efficiency parameter: η), while (7) constrains the maximum state of energy to the nominal battery energy capacity. The charging and discharging efficiency are jointly represented in one round-trip efficiency. This approach was motivated by the article [30], where the single overall energy efficiency was accurately determined from the experimental data. Maximum charging and discharging constraints (3)-(4) state that both variables need to be under, or equal to the maximum allowed charging/discharging power. Binary variables ensure that the maximum allowed power is set to zero if current battery mode is different form the mode of the respective variable (e.g. power discharging variable should not be greater than zero if battery is charging), while it is set to the allowed maximum power, when both modes of the battery and variable match each other. Constraint (5) ensures that charging and discharging modes aren't active at the same time. This constraint might be even unnecessary if efficiency coefficient (η) is lower than one (which in general it is), but it is stated for the sake of completeness. The requirement that the state of energy at the end of the observed period is at least as at the beginning is incorporated in the model using constraint (6) Non-negativity of the variables is ensuring constraint (8). Constraints (2)-(5) very vaguely describe the process of charging and discharging the battery, as this UCS is based on precision, the model is further extended with the Reducing Charger Power (Linear CC-CV) concept [29]. It is a more accurate representation of the battery charging power constraint where charging capacity is reduced after switching to the constant-voltage mode when charging a battery. The linear form of the charging power dependency on the battery state of energy is formulated as in [29], [30]:

$$p_t^{ch} \leq \frac{CHAR^{max}}{\eta^E} \cdot \frac{C^E - soe_t}{C^E - SOE^{CC,CV}}, \qquad \forall t \in T \ (10)$$

It fits perfectly as an additional constraint to the (1)-(9) problem formulation. (10) acknowledges the reduced charging capacity after switching to the constant-voltage mode when charging a battery. $SOE^{CC,\,CV}$ is a parameter which contains battery state of energy at which the constant-current charging regime changes to the constant voltage regime. After reaching the state of energy denoted in $SOE^{CC,\,CV}$, constraint (10) becomes binding (stricter than (3)), and charging limit is decreased in a linear manner from $CHAR^{max}$ to zero. So, the linear CC-CV model consist of objective function (1) and constraints (2)-(10).

Even more accurate representation of a battery is one from [30]. They introduce model with energy charging limit and it perfectly fits the needs of this use case scenario.

$$soe_t = \sum_{i=1}^{I-1} soe_{t,i}, \qquad \forall t \in T \; (11)$$

$$soe_{t,i} \leq R_{i+1} - R_i, \qquad \forall t \in T, i \in I \; (12)$$

$$\Delta soe_t = F_1 + \sum_{i=1}^{I-1} \frac{F_{i+1} - F_i}{R_{i+1} - R_i} \cdot soe_{t-1,i}, \qquad \forall t \in T \; (13)$$

$$p_t^{ch} \leq \frac{\Delta soe_t}{\Delta t \cdot \eta^E}, \qquad \forall t \in T \; (14)$$

The objective function (1) stays the same, while in addition to the constraints (2), (4)-(9) constraints (11)-(14) are introduced. Variable *Δsoe* denotes amount of energy that can be charged into the battery in the following time step (in this use case, one hour is chosen as a time step) depending on the previous state of energy. This dependence is obtained from measuring battery characteristics in a laboratory (CC-CV characteristic). It is non-linear, so to fit this model it should be approximated by a piecewise linear function that results in 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 (10). Constraint (11) limits energy of each segment, while (12) determines maximum energy charging ability of the respective battery at each time period. Finally, (13) is maximum charging power constraint.

3.3.2 DLFM optimization problem

The second optimization problem introduces opportunity for a profit-oriented ESP to respond to the FlexRequest issued by the respective DSO. As the ESP has already submitted its schedule after the day-ahead market clearing time, possible schedule deviations are to be adjusted via balancing market. Having as input DA schedule and knowing both prices on the Flexibility and Balancing market, ESP needs to optimize its schedule so the OPEX stays as low as possible. The objective function of the second optimization problem (14), consists of the player's action on the DLFM and BM, as DAM is already cleared (R-DLFM configuration), it is not included in the objective function, but in constraints.

$$Max \sum_{t=1}^{24} -dev_t^{ch} \cdot BLNC_t^{\downarrow} - dev_t^{dch} \cdot BLNC_t^{\uparrow} + flex_t^{\uparrow} \cdot FLEX_t^{price,\uparrow} - flex_t^{\downarrow} \cdot FLEX_t^{price,\downarrow},$$

$$\forall t \in T \; (15)$$

Variables *dev*^{ch} and *dev*^{dch} represent deviations from the DA schedule that are then adjusted on the Balancing market, while both *flex* variables represent upward and downward flexibility services provision, respectively. And such services are compensated from flexibility user on a flexibility market under *FLEX* prices.

$$SOE_t = SOE_{t-1} - \left(p_t^{dch,PRM} - dev_t^{dch} + flex_t^{\uparrow}\right) \cdot \Delta t^h + \left(p_t^{ch,PRM} - dev_t^{dch} + flex_t^{\downarrow}\right) \cdot \eta^E \cdot \Delta t^h, \quad \forall t \in T \; (16)$$

$$p_t^{dch,PRM} - dev_t^{dch} + flex_t^{\uparrow} \leq DISCH^{max}, \quad \forall t \in T \; (17)$$

$$p_t^{dch,PRM} - dev_t^{dch} + flex_t^{\uparrow} \geq 0, \quad \forall t \in T \; (18)$$

$$p_t^{ch,PRM} - dev_t^{dch} + flex_t^{\downarrow} \leq CHAR_{max}, \quad \forall t \in T \; (19)$$

$$p_t^{ch,PRM} - dev_t^{dch} + flex_t^{\downarrow} \leq 0, \quad \forall t \in T \; (20)$$

$$flex_t^{\downarrow} \leq FLEX^{req,\downarrow}, \quad \forall t \in T \; (21)$$

$$flex_t^{\uparrow} \leq FLEX^{req,\uparrow}, \quad \forall t \in T \; (22)$$

Constraints (16)-(22) are the most important constraints for the optimal scheduling problem considering DAM, FM and BM. Three variables that result in the battery's charging schedule are: $p^{ch,PRM}$ – parameter coming from the DA schedule, *dev*^{ch} and *flex*^{down}, they are represented by single variable to formulate constraints in the same manner as in (10) - linear CC-CV concept and (11)-(14) – energy charging limit model. More precisely, if constraints (23) and (24) are introduced, the second optimization problem may be observed in the same manner as in the first optimization problem, but having in mind objective function (15),

$$p_t^{dch} = flex_t^{\uparrow} + p_t^{dch,PRM} - dev_t^{dch}, \quad \forall t \in T \; (23)$$

$$p_t^{ch} = flex_t^{\downarrow} + p_t^{ch,PRM} - dev_t^{ch}, \quad \forall t \in T \; (24)$$

3.4 Algorithmic solution

The formulated two-stage linear single-level problem may be solved by almost any of the commercially available solvers. Two optimization problems are run consequently one after another. Although, in reality *soe-Δsoe* characteristic is non-linear, the used model does not contain any non-linearities, as piece-wise linearization was used (see equations (11)-(13)).

3.5 Simulation setup and performance evaluation results

3.5.1 Simulation setup

This section presents preliminary studies of the performance of our proposed mathematical model and algorithm. The algorithm is written and run in Python using Gurobi Optimizer version 9.0.2. All simulations were performed on a personal computer with Intel Core i7 1.80 GHz and 16 GB RAM.

The capacity of the battery storage unit considered for the purposes of simulation setup and performance evaluation is 10 MWh. Its full charge/discharge efficiency (η^E) is 0.81. While the initial state of energy is 50%. Three markets are observed: a) DAM, b)DLFM and c)BM. DAM and BM data have been fetched from the NordPool website [31] (specifically the Danish electricity market), while prices for the DLFM were randomly generated (in such a manner not to be too far from the DA prices) as such market is still a hypothetic one. In further months, different DLFM price scenarios will be analyzed in a much-detailed manner. Simulation considered a daily (24h) time horizon.

3.5.2 Performance evaluation process

In this state of the use case scenario development, the emphasis was put on different battery representation models. Three approaches are compared, and initial conclusions written:

- Constant Charging Power Limit
- Reducing Charging Power (Linear CC-CV Model)
- Energy Charging Limit

3.5.2.1 First optimization problem

Regarding the first optimization problem, the one including only DA market. Table 5 shows the profit of participating on DAM for all three cases.

Table 5: DAM profit for three BSU modelling approaches

APPROACH	CONSTANT CHARGING POWER LIMIT	REDUCING CHARGING POWER (LINEAR CC-CV MODEL)	ENERGY CHARGING LIMIT
PROFIT [€]	518	502	512

As it is shown in the above table, the most inaccurate approach (constant charging power limit) results in the highest profit, laboratory (pilot) test should show that this cannot in reality be achieved as battery charging and discharging curves aren't capable of following such schedule. On the other hand, the Linear CC, CV model is considered as the most conservative one among these three. DAM profit results support that claim, as the result of 502€ is lowest comparing all of the three approaches. Although conservatism may be helpful and even wishful in some occasion, we utilized also the third type of approach which is labeled as the most accurate one. For the Energy charging limit approach, the profit is between above two figures confirming conservatism of the Linear CC-CV approach and unreal optimism (which in reality may result with higher volumes that should be balanced on the BM, hence higher costs) of the constant charging power limit.

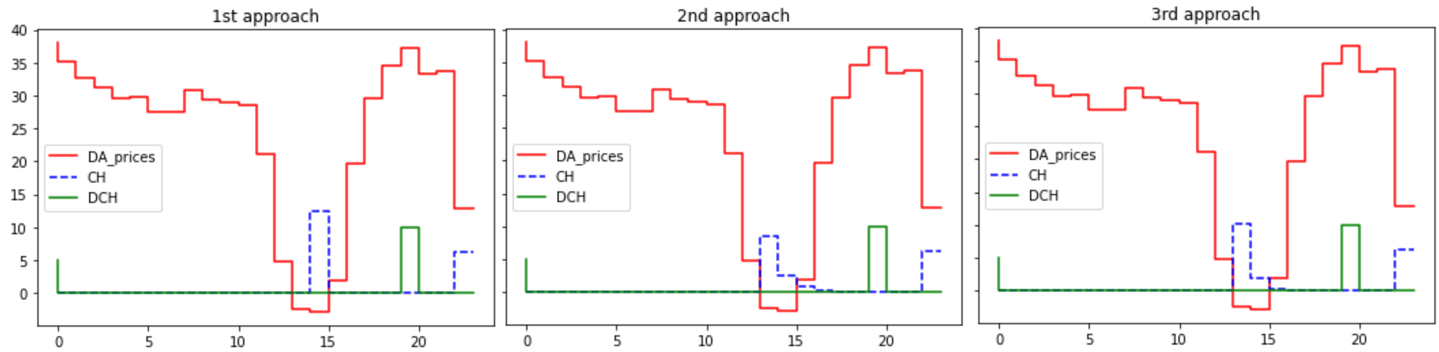


Figure 15: Charging and discharging graphs for all three approaches

In the Figure 16, it is clearly shown that for the given DAM prices, all three approaches have similar timing, with small differences in the exchanged volumes of energy. Charged and discharged volumes of energy follow the same distribution as the expected profits from the above attached table. To have a better quantitative understanding, table 6 denotes hourly yield of the profit-oriented ESP for every hour in the observed period. One may notice that the general modus operandi is pretty similar (as already stated), but battery activities differ from approach to approach. Finally, the schedules calculated in this run of the optimization are then sent to the 2nd round, where they are considered as input parameters.

Table 6: Profit/cost per hour for all three approaches

Hour	1st approach	2nd approach	3rd approach
0	190	190	190
1	0	0	0
2	0	0	0
3	0	0	0
4	0	0	0
5	0	0	0
6	0	0	0
7	0	0	0
8	0	0	0
9	0	0	0
10	0	0	0
11	0	0	0
12	0	0	0
13	0	0	0
14	0	21.0	25.0
15	0	7.4	5.3
16	0	-1.6	-0.5
17	34.8	-4.9	-0.7
18	0	-2.3	-0.1
19	0	0	0
20	372.5	371.5	372.5
21	0	0	0
22	0	0	0
23	-78.9	-78.9	-78.9

3.5.2.2 DLFM optimization problem

In the 2nd optimization problem, the DAM schedule is considered as input. The profit-oriented ESP may participate in the DLFM and consequently in the Balancing Market (to adjust its reported schedule if it was altered). Table 7 presents profits from participating on the DLFM and BM for all three approaches, as the DAM schedule is given as an input parameter, profits on the DAM are fixed from the previous optimization problem. Once again, the most conservative method (Linear CC-CV) yields the smallest profit, and the most precise one, energy charging limit concept, simulates somewhat smaller profit than that in the Constant charging power limit method.

Table 7: Profits in the 2nd problem for all three approaches

Approach	Constant Charging Power Limit	Reducing Charging Power (Linear CC-CV Model)	Energy Charging Limit
Profit [€]	703	689	699

Compared with the profits in the first optimization problem, it is obvious that DLFM (under prices in this scenario) in combination with the BM provided average profit increase for the ESP of about 40%. This may be understood as a great incentive from the ESP's point of view to participate in such market, assuming the ESP also exhibits optimal BM scheduling procedures so that the cost of balancing does not erase all gains from the offered flexibility in the DLFM.

Figure 17 illustrates Balancing Market prices (two lines) and profit/cost measured participation of the profit-oriented ESP in the BM. BM_UP denotes up regulating power prices, while BM_DOWN denotes down regulating power prices and each of the three bar colours in each hour present one of the three approaches. As one might notice, all three approaches follow the similar pattern and even benefit sometimes from the negative prices (light blue line). It is important to notice that at this moment it was assumed that both DLFM prices and BM market prices were known in the same moment. In that manner the scheduling algorithm optimized the operation of the BSU to take advantage of those two markets in best possible manner. Future work will deal in a greater detail with possible uncertainties in the moment when the ESP needs to take a decision on how to schedule its FlexAssets.

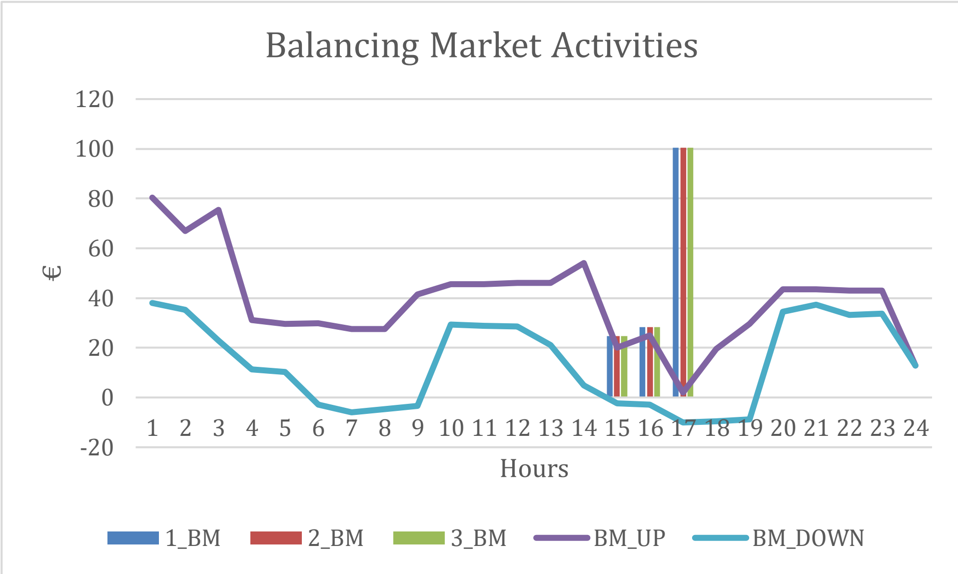


Figure 16: Balancing Market Prices and ESP participation activities

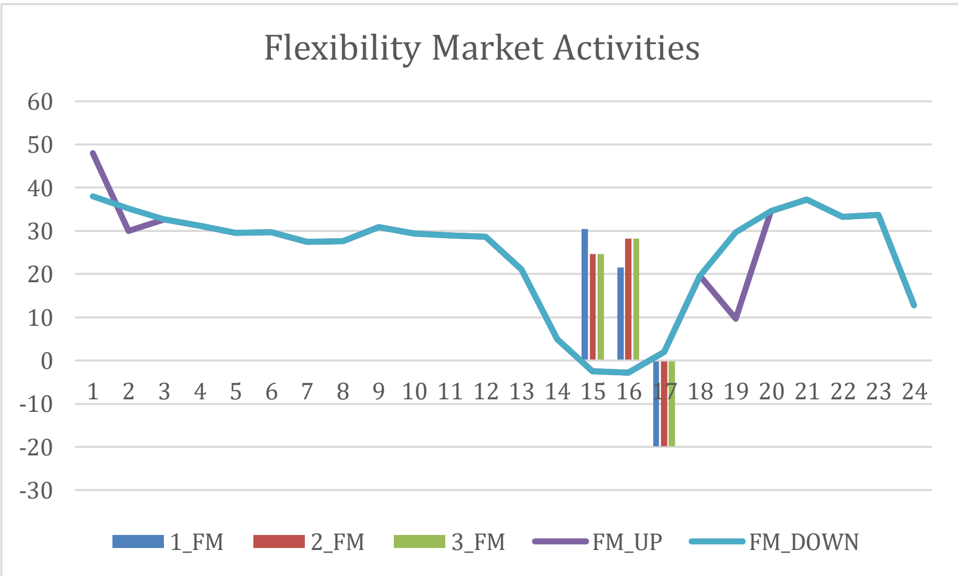


Figure 17: Flexibility Market prices and ESP participation activities

In the same manner, as for the Balancing Market, analysis has been conducted also for the Flexibility Market. For the prices generated in this example, one may notice how the optimization algorithm uses occurrence of negative prices to make profit, or low FM_DOWN prices to charge the battery with minimal cost. FM_UP prices aren't so attractive to offer the ESP even bigger incentive to participate in the FM, but this remains to be analysed in future months.

3.6 Next steps

Within M19-M26, we will analyze this topic in more detail, testing the proposed algorithm and its alternative versions. There will be a lot of testing with different scenarios (e.g. different combination of prices etc.). Furthermore, for the purposes of WP4 work, some of the characteristics may be broadened and not only BSUs considered. The idea is to test the mathematical model and algorithm in various markets and under different conditions to validate its generality and usefulness as part of the FLEXGRID ATP platform. In that manner, we shall obtain available data also from other countries (this example used NordPool's data for Denmark).

Task related with the respective WP6 work is to integrate the proposed optimal scheduling algorithm into the FlexSupplier's Toolkit (FST) and FLEXGRID ATP platform. This will enable the ESP user to run optimal scheduling algorithm in an online operating mode using the data from the ATP's Central Database or adding their own. While in the offline mode, the ESP user will have the opportunity to run various "what-if" scenarios testing different setups and to realize consequences of specific actions and setups. We believe that this might be of great assistance to the ESP when considering new business strategies for participation on different (and new) markets.

4 ESP's CAPEX minimization problem

The focus of this chapter is the research problem of the FLEXGRID's HLUC_02_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[5]
- 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.

Within WP4 context, we develop the mathematical model, the algorithm and conduct system-level simulations at TRL 3. The main goal is to integrate the UCS 2.2 algorithm in the FLEXGRID ATP (TRL 5). More precisely, in the FlexSupplier's Toolkit (FST) following a similar methodology like UCS 2.1 and UCS2.3.

Via FST, the ESP user is assumed to participate in four different markets. Namely, day-ahead market (DAM), reserve market (RM), distribution level flexibility market (DLFM) and balancing market (BM). **User may only use the offline operation mode** where various "what-if" simulation scenarios are run assuming various mixes of FlexRequests and FlexAsset portfolios. The ESP user assumes a given OPEX reduction target (e.g. 5%) and the optimal siting and sizing algorithm determines optimal investment strategy to achieve it.

4.1 Problem statement, related state-of-the-art and FLEXGRID research contributions

Observing the current trends in the domain of power supply, few general observations are non-negligible:

- Penetration of the intermittent energy resources [32]
- Distributed paradigm opposed to the centralized [33]
- Greater usage of modern energy storage solutions [34] due to:
    - Advancements in technology (e.g. [35])
    - Lower costs-economies of scale [36]–[38]
    - Orientation from fossil fuels towards greener solutions (e.g. in European Union – *Clean Energy for all Europeans package* [11]
- Demand seasonality in some regions (e.g. touristic attractions) [39]
- Increasing share of EVs (thus greater power supply demand) [40]

[5] https://nodesmarket.com/market-design/

But, perhaps the most important fact is that modern energy market paradigm offers the interested and eligible parties the opportunity to participate in it. Except natural monopolies such as transmission and distribution that have stayed regulated service and non-discriminatory towards any interested party, the tendency for other power system constituents is to be based on an open market structure. Of course, barriers there also exist in the form of: i) technical ii) legislative or economic requirements. Hence, 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 b) 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.

Siting and sizing problems are widely researched topic, hence various papers are available in the international literature. Most of them consider solely energy storage systems with the first big distinction among them whether they observe the problem on the transmission [41]–[43] or distribution level [44]–[46].

[41] uses DC optimal power flow to investigate how optimal siting, operation and optimal sizing of the heterogenous storage portfolio influences primarily OPEX. Results indicate the distinction between energy- and power-based storage technologies (hydro storage vs. flywheel) with the note that given various congestion situations and existing storage portfolios, hybrid behaviour also presents a viable solution. Pandzic et al. in [42] nicely compare the optimal storage siting and sizing problem with the transmission expansion problem. They argue that transmission lines move energy in space, while storage moves energy in time. They use three-stage mixed integer linear program (i.e. planning procedure) with DC lossless representation of the transmission network to identify the optimal locations and parameters of distributed storage units. Dvorkin et al. approach the problem in a bit different way. They examine in [43] how network expansion plans affect merchant storage investment decisions. The proposed tri-level model demonstrates that optimal locations are in proximity of RES, congested lines, and bulk conventional transmission. Furthermore, potential transmission expansion may eliminate some of the profit opportunities, but from the system perspective co-planning of storage and transmission expansion achieves greater operating cost savings than solely the deployment of storage. Opposed to the previous

articles, Hassan and Dvorkin consider optimally siting and sizing distributed energy storage units using bilevel program in the distribution network [44]. The upper level problem minimizes DSO's OPEX and CAPEX and models the distribution system constraints using SOCP-based AC power flow model, while lower level problem maximizes the social welfare and models transmission system constraints using a DC power flow model. Authors argue that energy storage resources located in distribution system benefit both distribution and transmission system if those two are coordinated. Regarding the DSO-TSO coordination, among other articles here will be mentioned work done by Vincente-Pastor et al. in [47], who investigate three different agents (DSO, TSO, retailer) procuring distributed energy resources, each for its own purposes. The results show that DSO-TSO coordinated procurement is more efficient dispatch than independent sequential procurements. It is interesting to add that the inclusion of the retailer in the coordination poses undesirable effects on DSO and doesn't improve social welfare. [45] brings review of energy storage allocation in distribution networks. Although, Zidar et al. did the mentioned review in 2015, it is still a high-quality basis about work done and open questions such as framework for simultaneous siting and sizing - which is also one of the problems considered in the scope of the FLEXGRID project. But not only energy storage systems are to be observed in the siting and sizing process. Throughout last two decades there was great number of published articles concerning distributed energy resources (e.g. [48]–[50]). To the best of authors' knowledge, in last couple of years the emphasize moved from DERs to the ESS, but lots of research is still being conducted in both directions. For instance, authors in [51] provide an approach based on chance-constrained programming of siting and sizing having as input analysis of stochastic models of wind power, solar output and load. Not all papers consider the economic factors; some observe only technical. In that manner, in [52], it has been shown how the integration of DERs (when they are optimally located and sized) may help in reducing voltage deviation and power losses. [53] proposes optimization method that aims to help integrating intermittent renewable energy units. As the case model wind farm was used and taking into consideration its stochasticity (Monte Carlo simulations of wind speed and load) genetic algorithm was used to solve the optimization problem.

Although a large number of articles explore siting and sizing problem both on the transmission and the distribution level, to the best of our knowledge, this is the first work to include a hypothetical DLFM in the model. Now, the optimal investment decisions are modeled considering DAM, RM, BM and DLFM characteristics. More specifically, the major contributions of this FLEXGRID UCS2.2 research are:

- Holistic approach to the problem (four markets considered, network topology, OPEX reduction targets, detailed FlexAssets' characteristics)
- Market price and RES generation forecasts are included in the model
- Integration of the proposed DLFM to the existing market architecture

4.2 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.

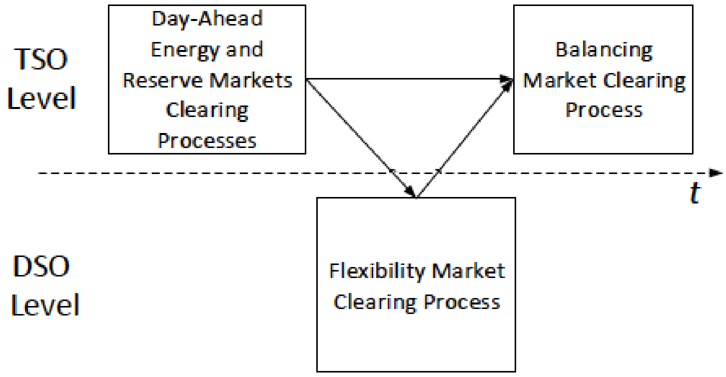


Figure 18: Proposed system model of the UCS 2.2

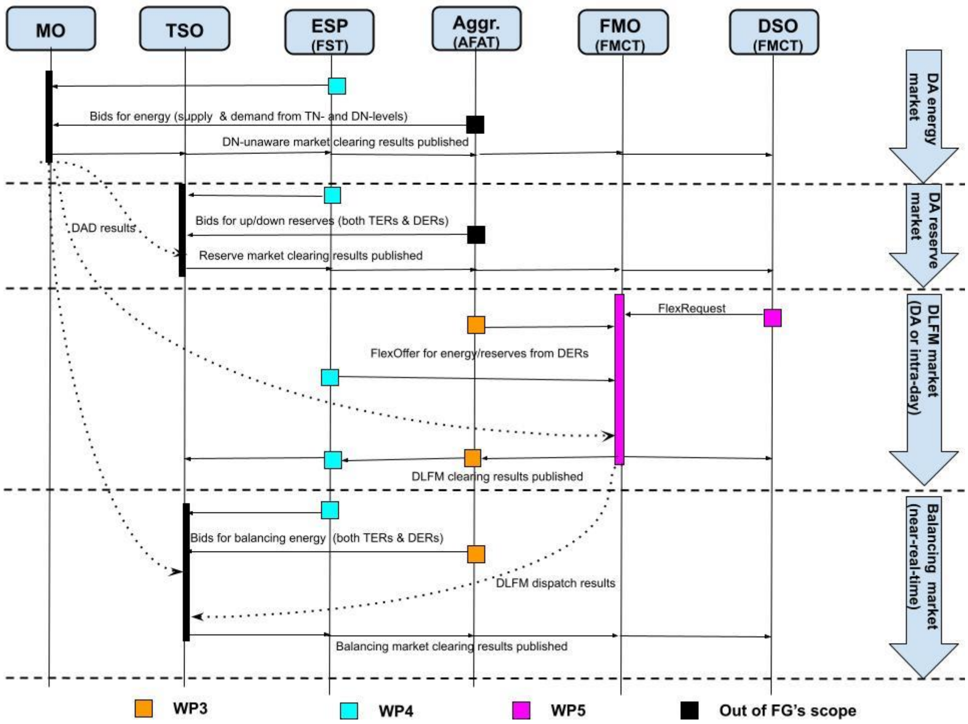


Figure 19: Placement of UCS 2.2 mathematical model and algorithm in the Reactive DLFM architecture proposed by FLEXGRID

Figure 20 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 20 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 as well as specific performance evaluation results (i.e.

sensitivity analysis) for various system-level simulation scenarios will be provided in following chapters and in a greater depth in the next deliverable.

4.3 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%). Hence, the cost function consists of both of the investment cost and the operational costs. Further research shall result with the final and more detailed form of the objective function. 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'[6] zone approach technique, where the whole distribution zone is divided into multiple zones and with relevant information (input data) revealed to the ESP. 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):

$$p_{ij} = \left[r_{ij} \cdot I_{ij} - P_j + \sum_{m:j\to m} p_{jm} \right] \quad (1)$$

$$q_{ij} = \left[x_{ij} \cdot I_{ij} - Q_j + \sum_{m:j\to m} q_{jm} \right] + v_j \cdot \frac{b_{ij}}{2} \quad (2)$$

$$v_j = v_i - 2 \cdot (r_{ij} \cdot p_{ij} + x_{ij} \cdot q_{ij}) + I_{ij} \cdot (r_{ij}^2 + x_{ij}^2) \quad (3)$$

$$I_{ij} \geq \frac{p_{ij}^2 + q_{ij}^2}{v_i} \quad (4)$$

$$p_{ij}^2 + q_{ij}^2 = S_{ij}^2 \quad (5)$$

$$P_i = \sum\nolimits_g p_{i,g} - \sum\nolimits_d p_{i,d} \quad (6)$$

$$Q_i = \sum\nolimits_g q_{i,g} - \sum\nolimits_d q_{i,d} \quad (7)$$

$$p_{i,g}^{min} \leq p_{i,g} \leq p_{i,g}^{max} \quad (8)$$

$$p_{i,g}^{min} \leq q_{i,g} \leq p_{i,g}^{max} \quad (9)$$

$$-S_{ij}^{max} \leq S_{ij} \leq S_{ij}^{max} \quad (10)$$

$$v_i^{min} \leq v_i \leq v_i^{max} \quad (11)$$

The BFM relaxes the standard model and takes primarily into consideration power and electricity flow through branches. Constraint (1) models the active power flow between the nodes (including ohmic loss), whereas constraint (2) models the reactive power flow. I_{ij} represents squared current value flowing through the branch *ij*, p_{ij} denotes active power flow through the branch, P_i sum of generation and demand in the node *i*, while the last term in (1) depicts power flow going in the downstream direction. The notation in (2) follows the same principle as (1), with the addition of shunt susceptance (last term). Constraint (3)

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

determines the squared voltage (v_i) per each node. Constraint (4) 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 (5) governs the relationship between active, reactive and apparent power. Constraints (6) and (7) sum active and reactive power and demand, respectively. The rest of the constraints (8)-(11) define minimal and maximal allowed values for active power, reactive power, apparent power and squared voltage. There is still an ongoing discussion about complete problem formulation, so in the following month the constraints will be updated and extended and in the D4.3 the final solution presented.

4.4 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 (4) if it were equality. To ensure the convexity of the optimization problem SOCP convex relaxation method was used and conic shaped area produced constrained by (4) replaced the non-convex shape which equality version of the constraint insists on. Further development of this use case scenario shouldn't bring any significant computational problems. 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.

4.5 Simulation setup and performance evaluation results

The research problem described in this chapter deals with four markets, namely: i) DAM, ii) RM, iii) DLFM and iv) BM. Therefore, their historical prices are needed as input. Combining WP3 and WP4 research efforts, historical market prices are also used to generate predictions on future prices for the respective markets. With important notice that the DLFM is non-existing market, so the "historical" prices are generated, and future price predictions don't have much sense. But, sensitivity analysis how different DLFM price scenarios affect ESP's business strategy will be of much help for evaluating pros and cons of the potential R-DLFM. All prices are observed on an hourly basis, so a vector of 24-hourly price values per selected day will be needed. Network topology is also required input, the format itself highly depends on the availability of such data, but general plan is to follow already mentioned NODES' zonal approach. Moreover, specifications both of current FlexAssets in ESP's portfolio and potential ones should be provided. Finally, OPEX reduction target (in percentage) is a necessary input parameter.

The main goal of the research problem described in this chapter is the ESP's CAPEX minimization for a given OPEX reduction target. The following KPIs will be of a great assistance to evaluate the performance of the proposed algorithm:

- **RES curtailment** levels. They should strive towards zero

- **Return on Investment** (ROI)
- Achieved **OPEX reduction**
- **CAPEX** amount
- **Overall costs** in an observed period (OPEX and CAPEX combined) – to assess is the OPEX reduction goal desirable
- **Revenues** per selected market and scenario

To easily integrate the algorithm with the FST, Python is used for all the programming work.

4.6 Next steps

Within M19-M26, we will elaborate on the UCS 2.2 work in order to further develop the optimal siting and sizing algorithm. Moreover, the emphasis will quickly shift to the system-level simulations to evaluate the performance of the proposed algorithm. Multiple case studies, other network topologies and other market data will be tested. Thus, we will be able to assess the performance of our proposed mathematical model and algorithm in more market and network setups.

Another research task, which is also related with the respective WP6 work is to integrate the proposed optimal siting and sizing algorithm into the FlexSupplier's Toolkit (FST) and FLEXGRID ATP. Thus, the ESP user will be able to utilize the FST to efficiently exploit available instruments to ensure reliable energy supply with the min. CAPEX. The ESP user will only be able to run the offline operation mode. There, the 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.

5 ESP's profit maximization by co-optimizing its participation in several energy and local flexibility markets

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 WP4 context, we develop the mathematical model, the algorithm and conduct system-level simulations at TRL 3. Our ultimate goal is to integrate the UCS 2.3 algorithm in the FLEXGRID ATP (TRL 5) and more specifically in the FlexSuppliers' Toolkit (FST) following a similar methodology like UCS 2.1 and 2.2 algorithms.

Via FST, the ESP user will be able to place optimal bids in 4 different markets. In an online operation mode, the ESP user will have the initiative. It will take market price forecasting data for 4 markets (i.e. day-ahead, reserve, DLFM, balancing) and will then calculate 4 optimal FlexOffers to submit in ATP. These FlexOffers will also be made instantly visible for the FMO user and DSO user. In the offline operation mode, the ESP user will be able to run various "what-if" simulation scenarios via running a stacked revenue maximization algorithm to identify how it can achieve maximum expected profits in the future.

5.1 Problem statement, related state-of-the-art and FLEXGRID research contributions

The ongoing decarbonization and decentralization of the electric power landscape delivers clean, sustainable and low-cost energy as well as energy autonomous societies. On the other hand, the rapid proliferation of distributed, variable and unpredictable generation can result in various challenges for the network operators, such as line and transformer congestion, voltage limit violations, and eventually dramatically increase the demand for flexibility [54]. Using the power system's flexibility instead of the costly network investments can create financial opportunities for the end users facilitating the integration of Renewable Energy Resources (RES). Thus, Distributed Energy Resources (DERs) can provide the necessary flexibility services to both the distribution (i.e. DSO) and the transmission level (TSO), as long as an economically efficient market environment is designed to motivate the investments in such technologies [55] .

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. 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.

Within FLEXGRID project's context, in order to address the aforementioned issues, the development of a Distribution Level Flexibility Market (DLFM) is proposed. A Flexibility Market Operator (FMO) clears the DLFM by minimizing the cost of acquiring the flexibility needed to ensure the participation of the DERs in the wholesale markets without jeopardizing the reliable operation of the distribution grid.

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).

There is a great deal of studies that have dealt with the problem of optimizing the multi-service portfolio of merchant-owned BSUs. Works in [15] and [56] studied the optimal bidding problem of a BSU in the day-ahead and real-time energy-only markets, while [57] and [58] dealt with energy storage devices participating in energy and frequency regulation markets. Authors in [59] and [60] studied the problem of optimal bidding and operating strategies for a storage owner participating in the energy and performance-based regulation markets. Similarly, [14] and [61] considered storage units participating in the day-ahead energy and reserve, as well as real-time energy and regulation markets. While the aforementioned works considered storage units that cannot affect the market prices and act only as price takers, works in [62] and [63] used bi-level programming to model the revenue maximization problem of a merchant storage owner that acts as a price maker in transmission-level energy and reserve markets. **All these works differ from our UCS 2.3 study, since they optimize the participation of storage units in only transmission-level energy and ancillary services markets.**

Another strand of research considered distributed BSUs that provide services to both the transmission and distribution systems. Authors in [64] consider a storage owner that is simultaneously participating in three markets: energy, TSO ancillary services and DSO (local congestion) market. The authors proposed a portfolio theory-based approach to decide on the optimal storage capacity allocated to each market in order to maximize the benefits at the minimum possible risk. The DSO services' remuneration is based on the congestion cost savings and is calculated based on a congestion cost index. Work in [65] formulated a Mixed-Integer Linear Program (MILP) to model the profit maximization problem of a storage that provides system–wide (energy arbitrage and system balancing) and local network services (peak demand shaving to alleviate the distribution network congestion). The DSO services' remuneration is assumed to be equal to the opportunity cost of the storage plant associated with the DSO's services, i.e. its revenue increase from the energy and balancing services markets, when no storage capacity is allocated to provide the DSO services. Work in [66] maximized the aggregate profits of energy storage providing energy, reserve and frequency regulation services to the transmission system and congestion management to the distribution grid. The distribution grid services are considered obligatory (and thus not voluntary based on a market-based context) and are not remunerated. A Model Predictive Control approach is examined in [67] to dynamically allocate storage power and energy capacities to either a local or a grid service with the objective of maximizing the profit of an energy storage aggregator. The energy storage profits result from energy price arbitrage and primary frequency control minus the costs of load curtailment reduction and transformer overheating. In [68], a generic formulation of the scheduling problem of a multi-service energy storage owner is designed. Based on this generic framework, the authors decide on the portion of energy and power to be allocated for dispatching the operation of a medium-voltage feeder and providing primary frequency control services. Finally, the authors in [69] proposed a joint optimization framework for energy storage units to reduce energy bills of commercial consumers (peak shaving) and seek profit through the provision of frequency regulation services. **Unlike these works, we consider a distribution-level marketplace, which determines the magnitude of the local grid services and their compensation through solving an Optimal Power Flow (OPF) problem.**

To the best of our knowledge, this is the first work to model the decision process of a strategic ESP owning distributed BSUs, that provides services both system wide and to the local DSO. More specifically, the major contributions of this FLEXGRID UCS 2.3 research are:

- In contrast to [64]–[69], it proposes a flexibility marketplace at the distribution level in order to calculate the optimal dispatch and compensation of local grid services. The proposed DLFM is introduced in the timeframe between the day-ahead energy market (DAM) and the near-real-time Balancing Market (BM) and is operated by an independent FMO entity (like NODES).
- It proposes a stacked revenues business model for distributed BSUs, which act as price makers in the existing Reserve Market (RM) and the proposed DLFM, while they cannot affect prices in the DAM and BM. It uses bi-level programming to model a strategic participation of a BSUs owner in both the TSO and the DSO markets.
- The bi-level model is solved by converting it into an Mathematical Program with Equilibrium Constraints (MPEC) using the Karush-Kuhn-Tucker (KKT) optimality conditions [70]. An iterative process is envisaged to deal with non-linearities that come from constraints that link decisions of the two markets.
- The IEEE 33-bus radial distribution system is used to evaluate the performance of our proposed bidding strategy. The results showcase that the proposed model achieves a super-linear gain, i.e. the ESP's profits are higher through co-optimized

TSO and DSO services' provisioning than the sum of individual profits coming from each of the two afore-mentioned services.

5.2 System model

This work proposes a market architecture in which the Distribution-Level Flexibility Market (DLFM) follows the clearing process of the distribution network-unaware day-ahead energy and reserve markets (intra-day timeframe), without changing the existing TN-level wholesale market structure (see figure below). The DLFM alters, if needed, the day-ahead energy market dispatch of the DERs participating in the TSO-level markets in order for the distribution network to operate safely within its limits. Consequently, the DERs will have to balance their portfolio through participating in the TSO's Balancing Market (BM). In this context, an ESP, which owns a set of BSUs located in different areas (nodes) of a radial distribution network, participates in all the aforementioned markets.

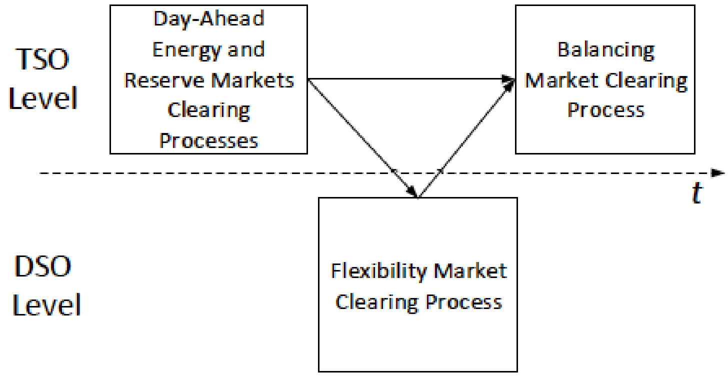


Figure 20: Proposed system model of FLEXGID UCS 2.3

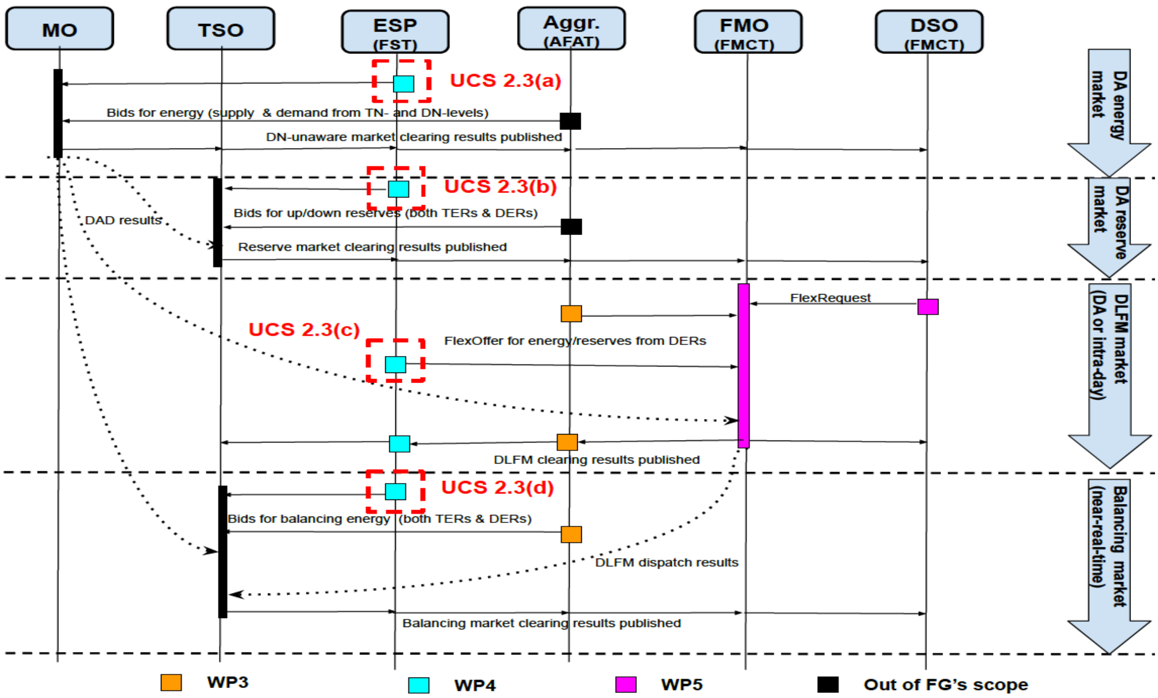


Figure 21: Placement of UCS 2.3 mathematical model and algorithm in the Reactive DLFM architecture proposed by FLEXGRID

As illustrated in the figure above, we consider the Reactive DLFM (R-DLFM) model, because it is compatible with the existing EU regulatory framework. This is the reason why we decided to implement UCS 2.3 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 DN-related problems such as local congestion and voltage control issues. With red outlines, it is shown the four co-optimized bidding decisions that are made by the ESP in order to maximize its profits. As it can be easily inferred, our proposed algorithm can also function well if we consider the existing regulatory framework (i.e. without the DLFM). However, in this case, the ESP's profits will be lower due to the less profit opportunities.

More technical details about all these issues as well as specific performance evaluation results (i.e. sensitivity analysis) for various system-level simulation scenarios are provided in the next sections.

5.3 Problem formulation

In order 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. In the upper level, the ESP decides on its bidding strategy, while taking as input the day-ahead energy prices and the balancing market forecasted prices. In the first lower-level problem, the RM clearing process takes place, while in the second lower-level problem, the DLFM clearing process takes place[7]. We assume that all the markets are cleared on an hourly basis. All these processes are mathematically modeled as follows:

5.3.1 Upper Level Problem: ESP's profit maximization

The upper-level (UL) problem maximizes the ESP's profits from its participation in various markets by selecting the optimal bidding/offering decisions and is formulated below in equations (a.1)–(a.17).

The objective function of the upper-level problem (a.1) maximizes the ESP's overall profits. The first line is associated with the DAM and RM profits of the ESP. Energy price is taken as an input (λ_t^e), while the upward/downward RM prices ($\lambda_t^{up}, \lambda_t^{dn}$) and the reserved quantities ($r_{i,t}^{s,up}, r_{i,t}^{s,dn}$) are obtained endogenously from the Lower-Level Problem 1 (cf. section 5.3.2 below). The second line in (a.1) is associated with the DLFM profit due to the provision of active and reactive power (P-flexibility and Q-flexibility) to the DSO. The DLFM nodal active and reactive locational marginal prices (i.e. P-LMPs and Q-LMPs) and the upward/downward P-flexibility and Q-flexibility dispatches are calculated endogenously in the clearing process of the DLFM (cf. section 5.3.3 below). Finally, since we consider that the DLFM follows the

[7] More details about this bi-level formulation structure are provided in previous D3.1 (https://flexgrid-project.eu/assets/deliverables/FLEXGRID_D3.1_final_version_29092020.pdf)

wholesale energy market (i.e. DAM), the active power DLFM dispatch concerning the ESP's BSUs will urge the ESP to readjust its energy market position by trading power in the near-real-time Balancing Market (BM). Thus, the last line in (a.1) represents the ESP's expected cost/profit from buying/selling in the BM the additional discharged/charged power (equal to the downward/upward P-flexibility provided in the DLFM by the BSUs). We assume that energy is traded in the BM at a single price ($\lambda^{b}_{t,\omega}$) as in [20]. In contrast to the wholesale energy market prices (λ^{e}_{t}), which can be predicted with high accuracy [21], the BM prices are highly volatile and thus considered stochastic in this work. We tackle this uncertainty via a finite number of scenarios. Finally, we assume that the power dispatch and the capacity commitment are planned in the day-ahead stage and the real-time stage decisions (such as the reserve activation) are outside the modelling scope.

$$\min_{X^{UL}} \sum_{t\in H} \Bigg(\sum_{i\in S} \Big(\lambda^{\mathrm{e}}_{t} \cdot (ch_{i,t} - dis_{i,t}) - \lambda^{\mathrm{up}}_{t} \cdot r^{\mathrm{s,up}}_{i,t} - \lambda^{\mathrm{dn}}_{t} \cdot r^{\mathrm{s,dn}}_{i,t} - \lambda^{\mathrm{P}}_{i,t} \cdot (p^{\mathrm{s,up}}_{i,t} - p^{\mathrm{s,dn}}_{i,t}) - \lambda^{\mathrm{Q}}_{i,t} \cdot (q^{\mathrm{s,up}}_{i,t} - q^{\mathrm{s,dn}}_{i,t}) - \sum_{\omega\in\Omega} \phi_{\omega} \cdot \lambda^{\mathrm{b}}_{t,\omega} \cdot (p^{\mathrm{s,up}}_{i,t} - p^{\mathrm{s,dn}}_{i,t}) \Big) \Bigg) \qquad \text{(a.1)}$$

Subject to

$$0 \le dis_{i,t} \le h_{i,t} \cdot \overline{S_i} \quad \forall i \in S, t \in H \qquad \text{(a.2)}$$

$$0 \le ch_{i,t} \le (1 - h_{i,t}) \cdot \overline{S_i} \quad \forall i \in S, t \in H \qquad \text{(a.3)}$$

$$h_{i,t} \in \{0,1\} \quad \forall i \in S, t \in H \qquad \text{(a.4)}$$

$$0 \le \widehat{r^{\mathrm{s,up}}_{i,t}} \le \overline{S_i} + (ch_{i,t} - dis_{i,t}) \quad \forall i \in S, t \in H \qquad \text{(a.5)}$$

$$0 \le \widehat{r^{\mathrm{s,dn}}_{i,t}} \le \overline{S_i} - (ch_{i,t} - dis_{i,t}) \quad \forall i \in S, t \in H \qquad \text{(a.6)}$$

$$0 \le \widehat{p^{\mathrm{s,up}}_{i,t}} \le \overline{S_i} + (ch_{i,t} - dis_{i,t} - \widehat{r^{\mathrm{s,up}}_{i,t}}) \quad \forall i \in S, t \in H \qquad \text{(a.7)}$$

$$0 \le \widehat{p^{\mathrm{s,dn}}_{i,t}} \le \overline{S_i} + (dis_{i,t} - ch_{i,t} - \widehat{r^{\mathrm{s,dn}}_{i,t}}) \quad \forall i \in S, t \in H \qquad \text{(a.8)}$$

$$E_{i,t} = E_{i,t-1} - (dis_{i,t} + p^{\mathrm{s,up}}_{i,t})/\eta^{\mathrm{d}}_{i} + \eta^{\mathrm{c}}_{i} \cdot (ch_{i,t} + p^{\mathrm{s,dn}}_{i,t}) \quad \forall i \in S, t \in H \qquad \text{(a.9)}$$

$$E_{i,t} + \widehat{r^{\mathrm{s,dn}}_{i,t}} \cdot \eta^{\mathrm{c}}_{i} \le \overline{E}_{i} \quad \forall i \in S, t \in H \qquad \text{(a.10)}$$

$$E_{i,t} - \widehat{r^{\mathrm{s,up}}_{i,t}}/\eta^{\mathrm{d}}_{i} \ge \underline{E}_{i} \quad \forall i \in S, t \in H \qquad \text{(a.11)}$$

$$E_{i,T} \ge E_{i,0} \quad \forall i \in S \qquad \text{(a.12)}$$

$$p^{\mathrm{BSS}}_{i,t} = dis_{i,t} - ch_{i,t} + p^{\mathrm{s,up}}_{i,t} - p^{\mathrm{s,dn}}_{i,t} \quad \forall i \in S, t \in H \qquad \text{(a.13)}$$

$$q^{\mathrm{BSS}}_{i,t} = q^{\mathrm{s,up}}_{i,t} - q^{\mathrm{s,dn}}_{i,t} \quad \forall i \in S, t \in H \qquad \text{(a.14)}$$

$$(p^{\mathrm{BSS}}_{i,t})^2 + (q^{\mathrm{BSS}}_{i,t})^2 \le (\overline{S_i})^2 \quad \forall i \in S, t \in H \qquad \text{(a.15)}$$

$$0 \le \widehat{q^{\mathrm{s,up}}_{i,t}}, \widehat{q^{\mathrm{s,dn}}_{i,t}} \le \overline{S_i} \quad \forall i \in S, t \in H \qquad \text{(a.16)}$$

$$c^{\mathrm{s,P,up}}_{i,t}, c^{\mathrm{s,P,dn}}_{i,t}, c^{\mathrm{s,Q,up}}_{i,t}, c^{\mathrm{s,Q,dn}}_{i,t} \ge 0 \quad \forall i \in S, t \in H \qquad \text{(a.17)}$$

Equations (a.2) and (a.3) state that the discharged/charged power that is sold/bought in the wholesale energy market is constrained by the inverter apparent power rating ($\underline{S_i}$). Binary variable $h_{i,t}$ indicates the operating mode of the BSUs; it equals 1 in the discharge mode and 0 in the charge mode (a.4). Constraints (a.5) and (a.6) state that the upward and downward reserve capacity provision are constrained by the scheduled discharged/charged power traded in the energy market and the inverter apparent power rating ($\underline{S_i}$). Additionally, the (upward/downward) P-flexibility provision to the DSO is constrained by the BSUs' apparent power rating and the energy and reserve schedules (cf. equations (a.7) and (a.8)). The BSUs' state of energy is calculated in Eq. (a.9), while Eqs. (a.10) and (a.11) define the BSUs' upward/downward reserve capacity provision capability. Equation (a.12) defines that at the end of the scheduling horizon, the BSUs' state of energy should be at least equal to their initial value. Each BSU is also controlled to inject/absorb reactive power. The overall active/reactive power schedules of the BSUs are presented in Eqs. (a.13) and (a.14), and should be calculated such that the apparent power at each timeslot does not exceed the apparent power rating, Eq. (a.15). Constraint (a.15) is linearized via a polygonal inner approximation. The Q-flexibility quantity bids of the BSUs are constrained in Eq. (a.16). Finally, Eq. (a.17) imposes non-negativity on the flexibility market price bids.

5.3.2 Lower-Level Problem 1: Day-Ahead Reserve Market Clearing Process

The Lower-Level Problem 1 represents the clearing process of the Reserve Market, which we assume is cleared independently from the energy market. The clearing process of the Reserve Market is formulated below in (b.1)–(b.7).

$$\min_{X^{RS}} \sum_{t\in H} \left(\sum_{i\in G} (\tilde{c}_{i,t}^{\text{g,up}} \cdot r_{i,t}^{\text{g,up}} + \tilde{c}_{i,t}^{\text{g,dn}} \cdot r_{i,t}^{\text{g,dn}}) + \right.$$
$$\left. + \sum_{i\in S} (c_{i,t}^{\text{s,up}} \cdot r_{i,t}^{\text{s,up}} + c_{i,t}^{\text{s,dn}} \cdot r_{i,t}^{\text{s,dn}}) \right) \tag{b.1}$$

Subject to

$$\sum_{i\in G} r_{i,t}^{\text{g,up}} + \sum_{i\in S} r_{i,t}^{\text{s,up}} \geq R_t^{\text{up}}; \quad (\lambda_t^{\text{up}}) \quad \forall t \in H \tag{b.2}$$

$$\sum_{i\in G} r_{i,t}^{\text{g,dn}} + \sum_{i\in S} r_{i,t}^{\text{s,dn}} \geq R_t^{\text{dn}}; \quad (\lambda_t^{\text{dn}}) \quad \forall t \in H \tag{b.3}$$

$$0 \leq r_{i,t}^{\text{g,up}} \leq \widehat{r_{i,t}^{\text{g,up}}}; \quad (\phi_{i,t}^{\text{gupmin}}, \phi_{i,t}^{\text{gupmax}}) \quad \forall i \in G, t \in H \tag{b.4}$$

$$0 \leq r_{i,t}^{\text{g,dn}} \leq \widehat{r_{i,t}^{\text{g,dn}}}; \quad (\phi_{i,t}^{\text{gdnmin}}, \phi_{i,t}^{\text{gdnmax}}) \quad \forall i \in G, t \in H \tag{b.5}$$

$$0 \leq r_{i,t}^{\text{s,up}} \leq \widehat{r_{i,t}^{\text{s,up}}}; \quad (\phi_{i,t}^{\text{supmin}}, \phi_{i,t}^{\text{supmax}}) \quad \forall i \in S, t \in H \tag{b.6}$$

$$0 \leq r_{i,t}^{\text{s,dn}} \leq \widehat{r_{i,t}^{\text{s,dn}}}; \quad (\phi_{i,t}^{\text{sdnmin}}, \phi_{i,t}^{\text{sdnmax}}) \quad \forall i \in S, t \in H \tag{b.7}$$

Objective function (b.1) minimizes the reserve capacity procurement cost based on the market participants' reserve prices and capacity offers. The upward/downward reserve requirements are enforced in eqs. (b.2) and (b.3), respectively. The dual variables of constraints (b.2) and (b.3) set the reserve up and down prices. Equations (b.4)–(b.7) limit the up and down reserve provision of the generators and the BSUs based on their respective offers. In this work, we assume that the rest of the RM participants form a competitive fringe and thus their price and quantity offers are treated as exogenous input parameters to our model. The dual variables pertaining to each constraint of the Lower-Level Problem 1 are specified at each constraint (b.2 – b.7) following a semicolon. The set of the primal variables of Lower-Level Problem 1 is $X^{RM} = \{r_{i,t}^{g,up}, r_{i,t}^{g,dn}, r_{i,t}^{s,up}, r_{i,t}^{s,dn}\}$.

5.3.3 Lower-Level Problem 2: DLFM Clearing Process

The Lower-Level Problem 2 represents the clearing process of the proposed Distribution Level Flexibility Market (DLFM). The ESPs bid their flexibility capacity ($\widehat{P^s} := \{\widehat{p_{i,t}^{s,up}}, \widehat{p_{i,t}^{s,dn}}, \widehat{q_{i,t}^{s,up}}, \widehat{q_{i,t}^{s,dn}}; \forall i \in S, t \in H\}$, $\widehat{P^r} := \{\widehat{p_{i,t}^{r,up}}, \widehat{p_{i,t}^{r,dn}}, \widehat{q_{i,t}^{r,up}}, \widehat{q_{i,t}^{r,dn}}; \forall i \in F_r, t \in H\}$) and cost ($C^s := \{c_{i,t}^{s,P,up}, c_{i,t}^{s,P,dn}, c_{i,t}^{s,Q,up}, c_{i,t}^{s,Q,dn}; \forall i \in S, t \in H\}$ and $\tilde{C}^r := \{\tilde{c}_{i,t}^{r,P,up}, \tilde{c}_{i,t}^{r,P,dn}, \tilde{c}_{i,t}^{r,Q,up}, \tilde{c}_{i,t}^{r,Q,dn}; \forall i \in F_r, t \in H\}$) to the FMO. 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). The DLFM clearing process is formulated below in equations (c.1) – (c.9).

$$\min_{X_{FM}} C^{s^{\mathrm{T}}} \cdot P^{s} + \tilde{C}^{r^{\mathrm{T}}} \cdot P^{r} \qquad \text{(c.1)}$$

Subject to

$$0 \leq P^{s} \leq \widehat{P^{s}}; \quad (\underline{\psi^{s}}, \overline{\psi^{s}}) \qquad \text{(c.2)}$$

$$0 \leq P^{r} \leq \widehat{P^{r}}; \quad (\underline{\psi^{r}}, \overline{\psi^{r}}) \qquad \text{(c.3)}$$

$$\sum_{k \in \Omega_d(n)} f_{nk,t}^{\mathrm{P}} = \sum_{j \in \Omega_p(n)} f_{jn,t}^{\mathrm{P}} - d_{n,t} + g_{n,t} - ch_{n,t} + dis_{n,t}$$

$$+p_{n,t}^{\mathrm{s,up}} + p_{n,t}^{\mathrm{r,up}} - p_{n,t}^{\mathrm{s,dn}} - p_{n,t}^{\mathrm{r,dn}}; \quad (\lambda_{n,t}^{\mathrm{p}}) \quad \forall n \in N, t \in H \qquad \text{(c.4)}$$

$$\sum_{k \in \Omega_d(n)} f_{nk,t}^{\mathrm{Q}} = \sum_{j \in \Omega_p(n)} f_{jn,t}^{\mathrm{Q}} - \delta_{n,t}^{\mathrm{d}} \cdot d_{n,t} + \delta_{n,t}^{\mathrm{g}} \cdot g_{n,t} +$$

$$q_{n,t}^{\mathrm{s,up}} + q_{n,t}^{\mathrm{r,up}} - q_{n,t}^{\mathrm{s,dn}} - q_{n,t}^{\mathrm{r,dn}}; \quad (\lambda_{n,t}^{\mathrm{q}}) \quad \forall n \in N, t \in H \qquad \text{(c.5)}$$

$$U_{n,t} = U_{j,t} - 2 \cdot (r_{jn} \cdot f_{jn,t}^{\mathrm{P}} + x_{jn} \cdot f_{jn,t}^{\mathrm{Q}}); \quad (\lambda_{n,t}^{\mathrm{v}})$$
$$\forall n \in N, j \in \Omega_p(n), t \in H \qquad \text{(c.6)}$$

$$\underline{V}_n \leq U_{n,t} \leq \overline{V}_n; \quad (\underline{\psi_{n,t}^{\mathrm{v}}}, \overline{\psi_{n,t}^{\mathrm{v}}}) \quad \forall (n,k) \in B, t \in H \qquad \text{(c.7)}$$

$$\underline{f^{\mathrm{P}}}_{nk} \leq f_{nk,t}^{\mathrm{P}} \leq \overline{f^{\mathrm{P}}}_{nk}; \quad (\underline{\psi_{nk,t}^{\mathrm{pf}}}, \overline{\psi_{nk,t}^{\mathrm{pf}}})$$
$$\forall (n,k) \in B, t \in H \qquad \text{(c.8)}$$

$$\underline{f^{\mathrm{Q}}}_{nk} \leq f_{nk,t}^{\mathrm{Q}} \leq \overline{f^{\mathrm{Q}}}_{nk}; \quad (\underline{\psi_{nk,t}^{\mathrm{qf}}}, \overline{\psi_{nk,t}^{\mathrm{qf}}})$$
$$\forall (n,k) \in B, t \in H \qquad \text{(c.9)}$$

The objective function of the Lower-Level Problem 2 (Eq. (c.1)) minimizes the flexibility procurement cost. Equations (c.2) and (c.3) bound the DLFM dispatch of the ESP ($P^s := \{p_{i,t}^{s,up}, p_{i,t}^{s,dn}, q_{i,t}^{s,up}, q_{i,t}^{s,dn}; \forall i \in S, t \in H\}$) and its competitors ($P^r := \{p_{i,t}^{r,up}, p_{i,t}^{r,dn}, q_{i,t}^{r,up}, q_{i,t}^{r,dn}; \forall i \in F_r, t \in H\}$) based on their capacity offers (i.e. FlexOffers)[8].

[8] See more details about the FlexOffer creation in UCS 4.3, which are provided in D3.2 (chapter 3).

Like in the RM, the competing ESPs' FlexOffers are treated as parameters; we assume that they form a competitive fringe (price takers). In order to model the distribution network, we use the linearized DistFlow equations (c.4)–(c.9) first introduced in [23]. Equations ((c.4) – (c.6)) are the branch flow equations. In (c.4) and (c.5), the local production ($g_{n,t}$) and demand ($d_{n,t}$) are decided in the DAM, which precedes the DLFM's clearing process, and thus are treated as parameters. Equations (c.7) – (c.9) set the lower/upper limits of the square voltage magnitude ($U_{n,t}$), active power flows ($f_{nk,t}^{P}$) and reactive power flows ($f_{nk,t}^{Q}$), respectively. The dual variables pertaining to each constraint of the Lower-Level Problem 2 are specified at each constraint ((c.2) – (c.9)) following a semicolon. The P-LMPs and Q-LMPs arise from the dual variables of constraints (c.4) and (c.5). They are non-zero in case of distribution network contingencies and denote the price at which the ESPs will be compensated for their P/Q-flexibility services required for the distribution network to operate within its technical limits (i.e. voltage and line thermal bounds). Positive DLFM prices indicate the need for supplying power to the grid, while negative DLFM prices imply the need for absorbing power by the ESPs.

5.4 Proposed algorithmic solution

The formulated non-linear bi-level problem can be solved using a duality-based approach. First, we replace problems (b) and (c) formulated above 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 [71]. The resulting single non-linear optimization problem is a Mathematical Program with Equilibrium Constraints (MPEC). We tackle the non-linearities using an exact linearization approach and the Big-M approach, as in [63] and [72]. The constraints that link variables from the two lower-level problems (b) and (c) cause the remaining non-linear terms in the objective function (as in [62] and [73]). More specifically, we need to linearize the terms $dis_{n,t} \cdot \lambda_{n,t}^{p}$ and $ch_{n,t} \cdot \lambda_{n,t}^{p}$. We use an iterative process to deal with these non-linearities as follows:

1. Replace non-linear terms $dis_{n,t} \cdot \lambda_{n,t}^{p}$ and $ch_{n,t} \cdot \lambda_{n,t}^{p}$ with linear terms $dis_{n,t} \cdot \underline{\lambda}_{n,t}^{p}$ and $ch_{n,t} \cdot \underline{\lambda}_{n,t}^{p}$, where $\underline{\lambda}_{n,t}^{p}$ is a constant. This constitutes our model linear and the resulting optimization problem is a MILP.
2. Initialize the iteration counter $v = 1$ and set $\underline{\lambda}_{n,t}^{p,v} = 0$.
3. Solve the MILP and calculate the optimal values $\lambda_{n,t}^{p,v^*}$ and the optimal objective function value ϕ^{v}. Set $\underline{\lambda}_{n,t}^{p,v} = \lambda_{n,t}^{p,v^*}$ and update iteration counter $v = v + 1$ and.
4. If $\phi^{v} - \phi^{v-1} \leq \epsilon$, with ϵ being a small real number, then stop the process. Otherwise, go to step 3.

5.5 Simulation setup and 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 [74] is illustrated in the figure below. 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 [75]. We considered two 2.5 MW x 1.6h BSUs, located at buses 24 and 30 in the distribution network (see figure below). 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 [76]. Data from Mavir, the Hungarian TSO [77], and the HUPX, the Hungarian Power Exchange [78], 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 [75]. Finally, a daily (24h) time horizon is considered.

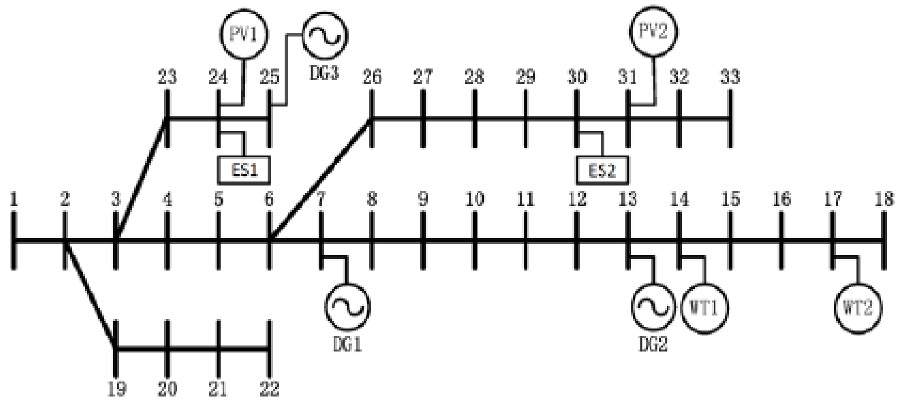


Figure 22: IEEE 33-node distribution system used for testing and performance evaluation purposes

5.5.2 Performance evaluation results

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

- **<u>Case 1:</u>** The ESP provides (energy and reserve) services to the TSO only through its participation in the DAM and RM.
- **<u>Case 2:</u>** 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.
- **<u>Case 3:</u>** 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.
- **<u>Case 4:</u>** The ESP participates in all four markets adopting the proposed model that co-optimizes the ESP's participation (and thus its expected profits) in all four markets.

In Case 1, the ESP's main target is to guarantee that the BSUs will maximize their combined (upward and downward) capacity available for offering in the FCR market, while simultaneously taking advantage of the most significant DAM price fluctuations. Hence, the

ESP trades energy in the DAM mainly to generate more profit opportunities in the RM. During the discharge hours, the ESP offers higher downward reserve capacity, while the BSUs' charging mode enables it to offer higher upward reserve capacity. The figure below illustrates the market breakdown of the ESP's revenues in each of the cases under investigation. In Case 1, the ESP gains 26.25€ in the DAM and 2417.9€ from providing ancillary services to the TSO, resulting in 2444.2€ overall profit.

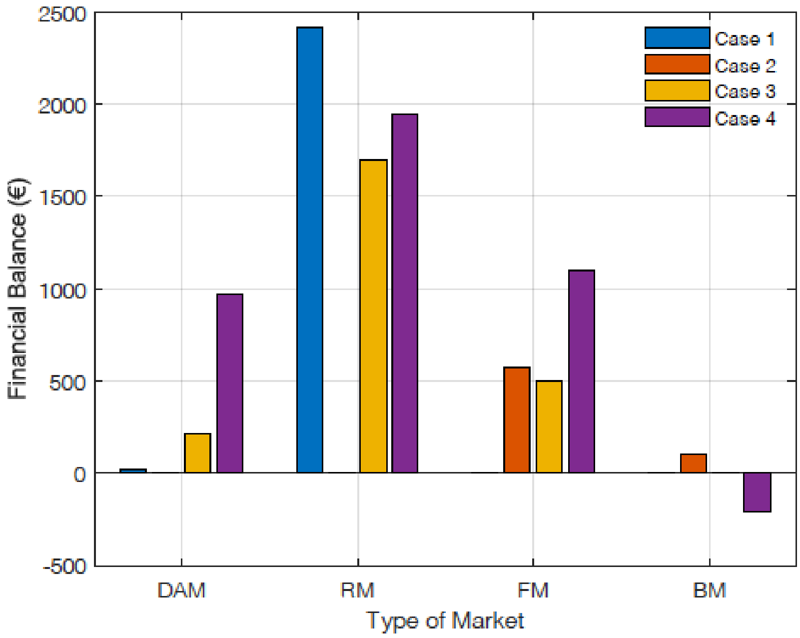


Figure 23: Financial balance per market in the cases under investigation

In Case 2, the ESP provides flexibility to the DSO, while taking into account the expected BM prices. Hence, its main objective is to offer upward P-flexibility services when needed by the DSO (positive P-LMPs) or when the BM prices are high, and downward P-flexibility services when profitable (i.e. the reward from the DLFM is greater than the penalty in the BM, i.e. $|\lambda^{\mathrm{P}}_{i,t}| \geq \sum_{\omega\in\Omega}(\phi_\omega \cdot \lambda^{\mathrm{b}}_{t,\omega})$). In parallel, the ESP offers upward or downward (depending on the sign of the Q-LMPs) Q-flexibility services to the distribution grid. Overall, the ESP gains a total of 674.04€ (571.81€ from the DLFM and 102.23€ from the BM).

In Case 3, the ESP initially decides on its energy trading in the DAM ignoring the profit opportunities that follow (participation in RM, DLFM and BM), resulting in the DAM profit of 217.67€. This "myopic" strategy hampers the BSUs' ability to offer reserve services through the FCR market. The RM profit for the ESP is 1669.7€, which is 30% lower than the RM gains of the ESP in Case 1. The ESP's bidding decisions in the RM do not consider its strategy in the DLFM, and hence the ESP's previous (DAM and RM) decisions leave the BSUs with neither upward nor downward active power capacity to offer to the DSO (see Eqs. (a.2) – (a.8)). Thus, the BSUs provide only Q-flexibility in the DLFM, which brings the ESP 498€ from its participation in the DLFM (lower by 13% than in Case 2). Since the ESP does not offer P-flexibility services, it does not participate in the BM. Ultimately, adopting a "myopic" behavior, the ESP gains a total profit of 2415.7€, which is 1.17% lower than Case 1, even if the ESP participates in all four markets, while in Case 1 it offers only energy and reserve services to the TSO.

In Case 4, the ESP attempts to take advantage of all business opportunities. First, note that at a certain timeslot, the BSUs' state of energy is determined by two components: i) the energy market decision ($dis_{i,t}/ch_{i,t}$), and ii) the DLFM active power dispatch ($p_{i,t}^{s,up}/p_{i,t}^{s,dn}$), see Eqs. (a.9), (a.13)). Thus, co-optimizing its stacked revenues from all markets, the ESP can perform market arbitrage between the DAM and the DLFM (discharge in the DAM and downward P-flexibility in the DLFM at the same timeslot and vice versa). Additionally, this strategy (offering energy and flexibility services of opposite directions) creates a space for highly profitable Q-flexibility services (see Eq. (a.15)). Also, the BSUs' active power schedule can create profit opportunities in the RM, by maximizing the available upward and downward reserve capacities (defined in Eqs. (a.10) and (a.11)).

The ESP's market behavior in Case 4 results in far higher DAM profits (974.09€ as shown in the figure above) than in the previous Cases, since the ESP's participation in the DLFM enables it to be much more active in the DAM. Additionally, the RM profits in Case 4 (1950.6€) are lower than in Case 1, but higher than in Case 3. This is justified by the fact that in Case 2, the RM is the main revenue source for the ESP that tries to maximize the reserve capacity offered to the TSO 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 that 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 derives 14.7% higher RM revenues. Moreover, the ESP's decisions bring 1101.7€ profit from the DLFM, which largely surpasses 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' active power services provision to the DSO, which modify the agreed energy schedule in the DAM, in a negative 210.94€ BM revenue, in contrast to Case 2, where the ESP earns 102.23€, and Case 3, in which the ESP does not participate in the BM. In the table below, the aggregate ESP's profits in all four Cases are presented. Our proposed strategy achieves a total gain of 3815.5€, which is super-linear, i.e. the revenues from jointly optimizing the BSUs' services to both the TSO and the DSO are higher 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, our model (Case 4) accomplishes 57.95% higher revenues than the "myopic" strategy (or else sequential market participation) of Case 3.

Table 8: Total ESP's profits per market participation case

	Case 1	Case 2	Case 3	Case 4
ESP's Profits (€)	2444.2	674.02	2415.7	3815.5

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 locations 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 2 and 3, ii) nodes 25 and 32 and iii) nodes 24 and 30. 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. 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 only for its Q-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 placed at nodes 25 and 32, 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 IEEE33-node test system in Figure 12) 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 32 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 2 (4120€), followed by location 3 (3815.5€) and location 1 (3358.2€) profits.

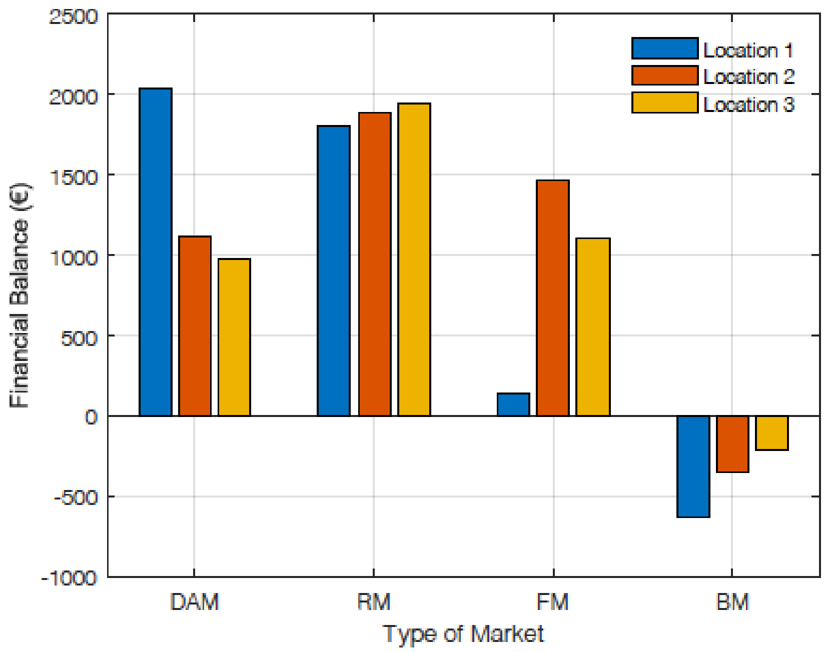


Figure 24: Breakdown of the ESP's market revenues for each BSU location under investigation

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, as in [76]. 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, while the DAM profits in Scenario 2 are higher than in Scenario 1, they plummet in Scenario 3. This is explained by the fact that in Scenario 3 the high 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 3, the ESP, in contrast with Scenarios 1 and 2, makes a small profit in the BM, 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 30.67% and 66.57% higher profits than in Scenario 1 (i.e. 4985.8€ and 6355.5€ as compared to 3815.5€).

Table 9: 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	30	6
Scenario 3	45	9

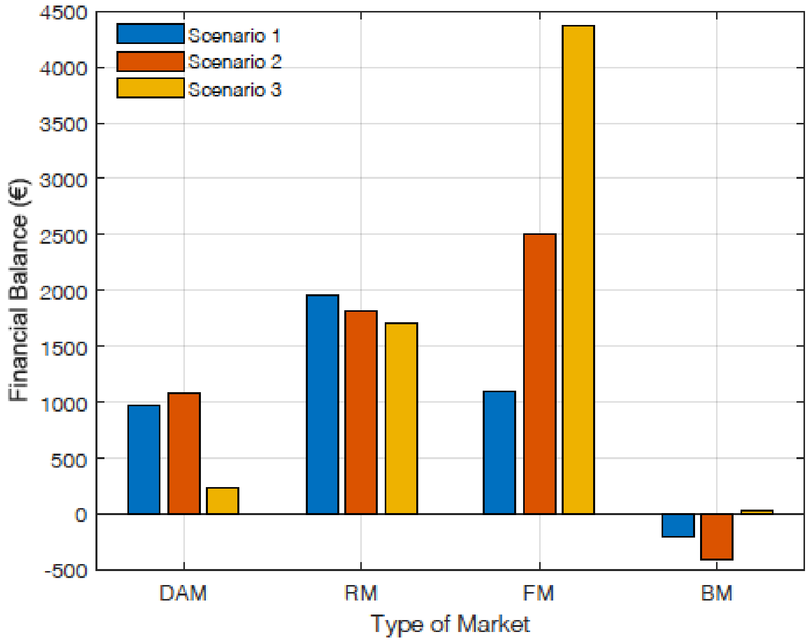


Figure 25: ESP's individual market revenues in each price offer scenario

5.6 Next research steps for M19-M26 period

Within M19-M26, we will elaborate on the UCS 2.3 work in order to convey more system-level simulations to evaluate the performance of our proposed algorithm by considering more case studies, other network topologies and other market data. Thus, we will be able to assess the performance of our proposed mathematical model and algorithm in more market and network setups. For example, until now, we have used Hungarian market data, but we will also conduct case studies with data from Nordic countries with the aid and consultancy of Nord Pool. We will also use other distribution network topologies and will investigate different BSUs' sizes, locations as well as sizes and locations of RES (e.g. new PV/wind parks).

Another research task, which is also related with respective WP6 work is to integrate the proposed stacked revenue maximization algorithm into the FlexSupplier's Toolkit (FST) and FLEXGRID ATP. Thus, the ESP user will be able to utilize the FST to place optimal bids in 4 different markets. In an online operation mode, the ESP user will have the initiative. It will take market price forecasting data for 4 markets (i.e. day-ahead, reserve, DLFM, balancing) and will calculate 4 optimal FlexOffers to submit in ATP. These FlexOffers should also be made visible for the FMO user and DSO user. In the offline operation mode, the ESP user will run various "what-if" simulation scenarios via running a stacked revenue maximization algorithm to identify how it can achieve maximum expected profits in the future. The important thing is that all this process will be automated and thus the ESP user will be able to exhaustively seek for new business opportunities, so that it can optimally utilize the FlexAssets that belong to its portfolio.

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

This chapter deals with the research problem of FLEXGRID UCS 2.4.

6.1 Problem statement, related state-of-the-art and FLEXGRID research contributions

In this UCS, we develop advanced models and algorithms 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 foreplay, namely:

- adopt imperfect market - aware bidding strategies to maximize their profits,
- respect the underlying network constraints, and
- take 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, while being responsible for respecting the distribution network constraints. This scenario perfectly fits BADENOVA's business in collaboration with its local DSO company BN-NETZE. As a matter of fact, there are many profit-based ESPs throughout Europe (such as BADENOVA), which are closely collaborating with their local DSO (BN-NETZE). Before the complete unbundling of the EU energy sector, these companies were operating a vertical business model, being thus responsible for both the distribution network operation and the trading of energy (i.e. purchasing energy from the wholesale market and selling it to end consumers). In the new EU-level liberalized energy markets' regulatory framework, an ESP's business is unbundled from the DSO's. However, 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).

Another interesting business case that can be also supported by UCS 2.4 is a Micro-Grid Operator (MGO) entity, which 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 may operate on behalf of the local energy community are:

- advanced models for the optimal MGO's participation in the existing energy markets
- 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
- optimal sizing, siting and operation for RES, Battery/Energy Storage System (BSS/ESS) and aggregated Demand Side Management (DSM) assets

The current status regarding the related research works from the international literature can be summarized in the following three main points:

- Current ESP's profit maximization models do not adequately model the competition with rival ESPs (i.e. market-aware bidding feature). This means that the ESP acts as a price-taker entity reducing thus the potential expected profits from market participation.
- The underlying distribution network topology is not taken into account for modelling optimal bidding strategies (i.e. network-aware bidding feature). This means that the ESPs may take bidding decisions that cannot then be realized in real-time, because of the distribution network constraints, which are continuously changing due to high RES penetration. Thus, the ESP may not be able to realize the expected revenues from its market participation.
- Current hybrid virtual power plant (VPP) scheduling and operation models do not take into consideration the heterogeneity of the various FlexAssets (i.e. optimal mix of DSM, ESS and RES assets). This means that more advanced models are needed in order to schedule the heterogeneous FlexAssets in a way that maximizes the ESP's revenues and also minimizes the expected capital expenditures (CAPEX) from a future new investment on FlexAssets in a given distribution network.

An extensive survey on related works from the international literature has been already documented in the previous D4.1. So, the interested reader may seek for more details in the references therein.

Conclusively, the major contribution of FLEXGRID UCS 2.4 is a holistic and sophisticated ESP's/MGO's business model that simultaneously:

- Offers price maker ESPs the capability to optimally bid in an imperfect electricity Day-Ahead Market taking into account the outer environment in terms of the decisions of electricity market competitors.
- Allows the adjustment and the respect of operational limits of a physical distribution network, ensuring that they will not be violated at any time. In this way, the ESP plans a distribution network–aware bidding strategy that saves it from high societal and monetary costs.

Orchestrates a virtual heterogeneous flexibility portfolio that comprises distributed renewable production, DSM and ESS units. The coordinated planning and scheduling of heterogeneous FlexAssets results in higher RES utilization and more cost-effective network operation.

6.2 System model

We consider a transmission grid, which is characterized by a set of buses V^G and a set of transmission lines $L \subseteq V^G \times V^G$. The transmission line between buses *i* and *j* is denoted by ij , $(i,j) \in L$. An ESP acts as an orchestrator/aggregator of heterogeneous FlexAssets over multiple geographically dispersed Distribution Networks (DNs). These DNs are connected to a set of buses of the transmission grid, denoted by $V^M \subseteq V^G$. For notational simplicity, a DN connected in bus *i* of the transmission grid is also indexed with *i*. RGs, ESSs, flexible (shiftable) and inflexible loads are located in each DN $i \in V^M$ turning it into a *VPP*, which can supply/draw power to/from the rest of the grid. More specifically, the DN connected to bus $i \in V^M$ is characterized by a set of nodes (DN buses) V_i, a set of edges (DN branches) $B_i \subseteq V_i \times V_i$, a set of ESSs S_i, a set of renewable generators R_i, a set of shiftable loads F_i and a set of inflexible loads A_i. Throughout this work, we refer to the edges of the transmission grid as lines and to those of a distribution network as branches, which are denoted by nk, $(n,k) \in B_i$, $i \in V^M$. The ESP is responsible for controlling the ESSs and the deferrable loads in order to strategically participate in the wholesale day-ahead energy market and maximize its profits. In addition, the ESP has to ensure the reliable operation of DNs. The goal of this work is to calculate the ESP's optimal bidding strategy in the day-ahead energy market and the optimal schedule of the heterogeneous FlexAssets, while simultaneously taking into account the distribution network constraints.

The following figure illustrates the system model under consideration as described above. In the upper part of the figure, the transmission network is depicted, while in the lower part, the distribution network is depicted. Within the FLEXGRID context, we consider three main network-related problems that may come up quite often in the future as a result of high RES penetration levels, namely:

- **Congestion may arise at the TSO-DSO coupling points (cf. green fonts).** For example, at certain timeslots within the day, local RES generation may exceed local demand and thus energy may not be able to flow from the distribution to the transmission grid.
- **Local congestion may arise within the distribution network (cf. blue fonts).** For example, when battery storage systems are not able to provide enough flexibility at certain timeslots, then local supply-demand imbalances may arise.
- **Local voltage control problems may arise within the distribution network (cf. red fonts).** This will happen mainly at the distribution network edges, because high RES generation may cause phenomena of reverse flows.

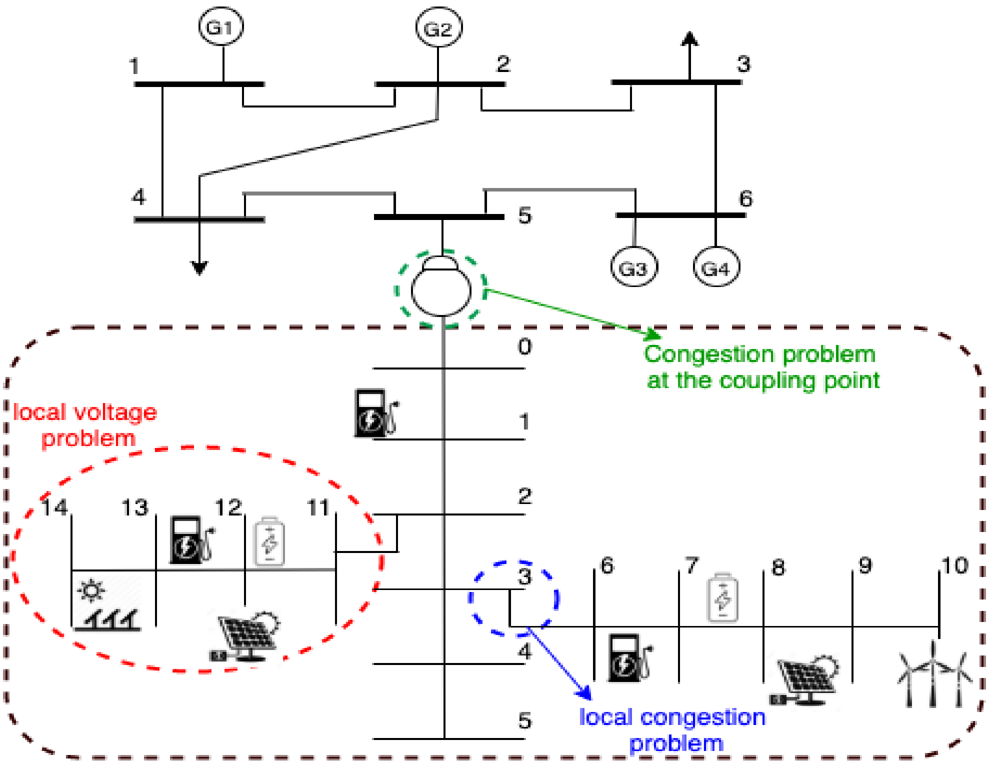


Figure 26: System model of FLEXGRID UCS 2.4

6.3 Problem formulation

Following up the descriptions of previous D4.1, we mathematically formulate our problem by modeling the following:

- Energy Storage Systems (ESS)
- Shiftable loads (DSM units)
- Underlying distribution network topology
- ESP's FlexOffers (i.e. quantity offers/bids)
- ESP's revenues and profits
- Day-ahead wholesale energy market clearing process

6.3.1 Modelling of Energy Storage Systems (ESS units)

Energy storage units is the first type of FlexAssets. As mentioned earlier, the ESP manages the ESSs' charging/discharging schedules. At each DN, $i \in V^M$ and timeslot $t \in H$, each ESS *s* (physical or virtual through the aggregation of several distributed battery systems) has to be charged or discharged. Charging (or discharging) power $r_{i,s,t}^{ch}$ $(or\ r_{i,s,t}^{dis})$ is limited by the ESS' maximum charging (or discharging) rate $r_{i,s}^{ch,max}$ (or $r_{i,s}^{dis,max}$, respectively). Thus:

$$0 \leq r_{i,s,t}^{ch} \leq \left(1 - x_{i,s,t}\right) \cdot r_{i,s}^{ch,max} \qquad \forall i \in V^M, s \in S_i, t \in H \qquad (1)$$

$$0 \leq r_{i,s,t}^{dis} \leq x_{i,s,t} \cdot r_{i,s}^{dis,max} \qquad \forall i \in V^M, s \in S_i, t \in H \qquad (2)$$

In (1) and (2), $x_{i,s,t}$ is a binary variable indicating the operating status (charging or discharging) of each DN's ESS at *t*. Thus, $x_{i,s,t} = 1$ when ESS *s* located in DN *i* is discharging at time *t* at *t,* and $x_{i,s,t} = 0$ when it is charging at time *t*. We denote by *H* = {1,2,…,*T*} the scheduling horizon considered. Additionally, the State of Charge $SOC_{i,s,t}$ of each ESS in DN *i* at any time interval *t* cannot exceed a lower bound $SOC_{i,s}^{min}$ and an upper bound $SOC_{i,s}^{max}$:

$$SOC_{i,s,t} = SOC_{i,s,0} - \sum_{\tau=1}^{t}(\eta_{i,s}^{d} \cdot r_{i,s,\tau}^{dis} - \eta_{i,s}^{c} \cdot r_{i,s,\tau}^{ch}) \qquad \forall i \in V^M, s \in S_i, t \in H, \qquad (3)$$

$$SOC_{i,s}^{min} \leq SOC_{i,s,t} \leq SOC_{i,s}^{max} \qquad \forall i \in V^M, s \in S_i, t \in H. \qquad (4)$$

In (3) and (4), the constants $\eta_{i,s}^{d}$ and $\eta_{i,s}^{c}$ denote the discharge and charge efficiency factors, respectively. In addition, we specify the final SoC of each ESS in order to take into account next day's operation:

$$SOC_{i,s,T} = w_{i,s} \cdot SOC_{i,s,0} \qquad \forall i \in V^M, s \in S_i\ . \qquad (5)$$

In (5), $w_{i,s} \geq 0$ is a design parameter (it is equal to 1 for a "neutral" ESS schedule).

6.3.2 Modeling of shiftable and curtailable loads (DSM units)

Shiftable (and curtailable) loads is the second type of FlexAssets in the hands of the ESP. Every shiftable load $d \in F_i, i \in V^M$, has a desired time schedule $\left[\alpha_{i,d}, \beta_{i,d}\right] \subseteq H$, within which it operates and must fulfill a specific task, meaning that a certain amount of energy $E_{i,d}^{fl}$ must be consumed by load d in that period. Outside this desired time interval, the power consumption of the shiftable loads is zero, while inside, it has an upper limit on its consumption rate ($p_{i,d}^{fl,max}$). Thus, the operating constraints of the shiftable load *d* in DN *i* are:

$$\{0 \le p_{i,d,t}^{fl} \le p_{i,d}^{fl,max},\ if\ t \in [\alpha_{i,d}, \beta_{i,d}]\ p_{i,d,t}^{fl} = 0, otherwise\ \forall i \in V^M, d \in F_i, t \in H \quad (6)$$

$$\sum_{t=\alpha_{i,d}}^{\beta_{i,d}} p_{i,d,t}^{fl} = E_{i,d}^{fl}, \qquad \forall i \in V^M, d \in F_i. \qquad (7)$$

6.3.3 Modelling of the underlying Distribution Network (DN)

The decisions made by the ESP must satisfy the DN's power flow constraints. In order to model the distribution network, we use the widely used by the literature linearized DistFlow equations from [74]:

$$\sum_{k\in\Omega_d^i(n)} p_{i,nk,t} = \sum_{j\in\Omega_p^i(n)} p_{i,jn,t} - p_{i,n,t}^{fl} - p_{i,n,t}^{infl} + p_{i,n,t}^{rg} + r_{i,n,t}^{dis} - r_{i,n,t}^{ch}$$
$$\forall i \in V^M, n \in V_i, t \in H \qquad (8)$$

$$\sum_{k\in\Omega_d^i(n)} q_{i,nk,t} = \sum_{j\in\Omega_p^i(n)} q_{i,jn,t} - \delta_{i,n}^{fl} \cdot p_{i,n,t}^{fl} - \delta_{i,n}^{infl} \cdot p_{i,n,t}^{infl} + \delta_{i,n}^{rg} \cdot p_{i,n,t}^{rg}$$
$$\forall i \in V^M, n \in V_i, t \in H \qquad (9)$$

$$U_{i,n,t} = U_{i,j,t} - 2 \cdot (r_{i,jn} \cdot p_{i,jn,t} + x_{i,jn} \cdot q_{i,jn,t})$$
$$\forall i \in V^M, n \in V_i, j \in \Omega_p^i(n), t \in H \qquad (10)$$

$$U_{i,n}^{min} \le U_{i,n,t} \le U_{i,n}^{max} \qquad \forall i \in V^M, n \in V_i, t \in H \qquad (11)$$

$$p_{i,nk}^{min} \le p_{i,nk,t} \le p_{i,nk}^{max} \qquad \forall i \in V^M, (n,k) \in B_i, t \in H. \quad (12)$$

$$q_{i,nk}^{min} \le q_{i,nk,t} \le q_{i,nk}^{max} \qquad \forall i \in V^M, (n,k) \in B_i, t \in H. \quad (13)$$

Equations (8), (9) and (10) are the *branch flow equations.* Thus, $p_{i,nk,t}$ and $q_{i,nk,t}$ denote the active and reactive power flowing in the branch nk connecting nodes $n \in V_i$ and $k \in V_i$. Furthermore, $p_{i,n,t}^{fl}, p_{i,n,t}^{infl}$, and $p_{i,n,t}^{rg}$ are the active powers of: flexible loads, inflexible loads and Renewable Generators (RGs) in node $n \in V_i$ at timeslot *t,* respectively. In addition, $\delta_{i,n}^{fl}$, $\delta_{i,n}^{infl}$ and $\delta_{i,n}^{rg}$ convert the active power of the shiftable loads, inflexible loads and RGs at node $n \in V_i$ into their reactive power ($\delta = tan(cos^{-1}(power\ factor))$. Furthermore $U_{i,n,t}$ is the square of the voltage, while $r_{i,jn}$ *and* $x_{i,jn}$ are the resistance and the reactance, respectively, of branch *jn* in DN *i*. Equation (11) imposes the lower ($U_{i,n}^{min}$) and the upper ($U_{i,n}^{max}$) limit on the voltage amplitude of node *n* in DN *i*. Finally, (12) and (13) constrain up ($p_{i,nk}^{max}$, $q_{i,nk}^{max}$) and down ($p_{i,nk}^{min}, q_{i,nk}^{min}$) the active and reactive power flows of branch *nk* in DN *i,* respectively. The sets $\Omega_d^i(n)$ and $\Omega_p^i(n)$ represent the decedent and precedent nodes, respectively, connected to node *n* in any radial DN. The root of each radial DN ($n = 0$), connected to the transmission grid, is the substation. In substations (where the power is sold/purchased to/from the market), the active and reactive power balance must hold:

$$\sum_{0k} p_{i,0k,t} = -p_{i,t}^{M} \qquad \forall i \in V^{M}, t \in H \qquad (14)$$
$$\sum_{0k} q_{i,0k,t} = -Q_{i,t} \qquad \forall i \in V^{M}, t \in H \qquad (15)$$

In (14), $p_{i,t}^{M}$ denotes the power that DN *i* supplies to the grid at timeslot *t*. A negative value of $p_{i,t}^{M}$ indicates that DN *i* draws power from the grid. In (15), $Q_{i,t}$ denotes the reactive power that *i* exchanges with the grid at timeslot *t*.

6.3.4 Modelling of the ESP's quantity offers/bids

In FLEXGRID's UCS 2.4, we assume a nodal wholesale electricity market, in which the ESP has to optimally choose for each DN *i* and time instants $t \in H$ its energy offer/bids ($o_{i,t}$, $b_{i,t}$). The latter are limited by each DN's total power net capacity (parameters $o_{i,t}^{max}$ and $b_{i,t}^{max}$):

$$0 \leq o_{i,t} \leq h_{i,t} \cdot o_{i,t}^{max} \qquad \forall i \in V^{M}, t \in H \qquad (16)$$
$$0 \leq b_{i,t} \leq \left(1 - h_{i,t}\right) \cdot b_{i,t}^{max} \qquad \forall i \in V^{M}, t \in H \qquad (17)$$

In (16) and (17), $h_{i,t} = 1$ if DN i sells power in wholesale market at t and $h_{i,t} = 0$ if it buys power.

$$o_{i,t}^{max} = \sum_{n \in R_i} p_{i,n,t}^{rg} + \sum_{n \in S_i} r_{i,n}^{dis,max} - \sum_{n \in I_i} p_{i,n,t}^{infl} \qquad \forall i \in V^{M}, t \in H \qquad (18)$$

$$b_{i,t}^{max} = -\sum_{n \in R_i} p_{i,n,t}^{rg} + \sum_{n \in S_i} r_{i,n}^{ch,max} + \sum_{n \in F_i} p_{i,n}^{fl,max} + \sum_{n \in I_i} p_{i,n,t}^{infl}$$
$$\forall i \in V^{M}, t \in H \qquad (19)$$

Equations (18) and (19) express the maximum quantity offer ($o_{i,t}^{max}$) and bid ($b_{i,t}^{max}$) that DN *i* can submit at time *t,* respectively. In (18) - (19), recall that R_i, S_i, A_i and F_i denote the sets of nodes in which RG, ESS, inflexible load and flexible loads are located in DN i, respectively.

Quantity offers/bids are also limited by the active power capacity of the coupling point between the DN *i* and the transmission grid (i.e. TSO-DSO coupling point):

$$o_{i,t}, b_{i,t} \leq \sum_{0k} p_{i,0k}^{max} \quad . \qquad (20)$$

Finally, the ESP decides on the price bid that DN *i* submits to the day-ahead market in timeslot *t*, which is denoted by $c_{i,t}^{M}$.

6.3.5 Modeling the ESP's profit maximization problem

In order for the ESP to schedule its heterogeneous FlexAssets in a network-aware and cost-effective manner, its profit maximization problem is defined as:

$$\max_{X_U} \sum_{t \in H} \sum_{i \in V^M} \lambda_{i,t} \cdot p_{i,t}^M$$
subject to the equations (1)-(20) (21)

In more detail, the objective of ESP is the maximization of its profits that result from its participation in the nodal electricity pool market. When a DN located at bus $i \in V^M$ supplies power to the grid at time t, it sells this power in the pool market at price $\lambda_{i,t}$, which is the nodal price 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 set of decision variables of ESP's problem (21) is $X_U = \{r_{i,s,t}^{dis}, r_{i,s,t}^{ch}, x_{i,s,t}, SOC_{i,s,t}, p_{i,d,t}^{fl}, p_{i,nk,t}, q_{i,nk,t}, U_{i,n,t}, Q_{i,t}, o_{i,t}, b_{i,t}, h_{i,t}, c_{i,t}^M \mid (i,s,t) \in V^M \times S_i \times H, (i,d,t) \in V^M \times S_i \times H, (i,(n,k),t) \in V^M \times B_i \times H, (i,n,t) \in V^M \times V_i \times H, (i,t) \in V^M \times H\}$. Hence, the ESP, given the production of the RGs and the inflexible loads that must run at any cost[9], decides on the quantity and price bids to the wholesale market, along with the optimal schedule of the ESSs and the flexible loads located at the DNs, in order to maximize its profits, while satisfying the DN constraints.

6.3.6 Modelling of the day-ahead wholesale energy market clearing process

As analyzed earlier, a nodal transmission-constrained electricity pool market is considered. Apart from the ESP, generators and demand aggregators participate in this market. The set of transmission grid buses in which generators are located is denoted by $G \subseteq V^G$ and the set of buses that demand loads are located is denoted by $D \subseteq V^G$. In ESP's optimization problem (21), dispatches and LMPs are calculated by the Market Operator (MO), which clears the day-ahead energy market. MO maximizes the Social Welfare by taking into account: i) the transmission grid constraints, ii) the participants' quantity offers/bids and iii) price bids. In other words, the MO decides on the energy dispatch schedules of the market participants (generators, demand aggregators and ESP) by solving a DC-OPF problem as follows:

$$\min_{X_L} \sum_{t \in H} \left(\sum_{i \in G} \left(c_{i,t}^g \cdot g_{i,t} \right) - \sum_{i \in D} \left(c_{i,t}^d \cdot d_{i,t} \right) + \sum_{i \in V^M} \left(c_{i,t}^M \cdot p_{i,t}^M \right) \right) \quad (22)$$

s.t. $-g_{i,t} + d_{i,t} - p_{i,t}^M + \sum_{j \neq \iota} y_{ij} \cdot \left(\theta_{i,t} - \theta_{j,t} \right) = 0 \ ; (\lambda_{i,t}) \ \forall i \in V^G, \forall (i,j) \in L, t \in H$ (23)

$$g_i^{min} \le g_{i,t} \le g_i^{max} \ ; \quad (\varphi_{i,t}^{gmin}, \varphi_{i,t}^{gmax}) \quad \forall i \in G, t \in H \quad (24)$$

$$-RD_i \le g_{i,t} - g_{i,t-1} \le RU_i \ ; \ (\varphi_{i,t}^{grd}, \varphi_{i,t}^{gru}) \quad \forall i \in G, t > 1 \quad (25)$$

$$-RD_i \le g_{i,t} - g_{,0} \le RU_i \ ; \ (\varphi_{i,t}^{grd}, \varphi_{i,t}^{gru}) \quad \forall i \in G, t = 1 \quad (26)$$

$$d_{i,t}^{min} \le d_{i,t} \le d_{i,t}^{max} \ ; \quad (\varphi_{i,t}^{dmin}, \varphi_{i,t}^{dmax}) \quad \forall i \in D, t \in H \quad (27)$$

$$-b_{i,t} \le p_{i,t}^M \le o_{i,t} \ ; \quad (\varphi_{i,t}^{mmin}, \varphi_{i,t}^{mmax}) \quad \forall i \in V^M, t \in H \quad (28)$$

[9] Note that we assume that RES spillage should be zero. We could also have a non-zero constraint for RES spillage or curtailment in order to model real-life business cases that happen nowadays.

$$-T_{ij}^{max} \leq y_{ij} * (\theta_{i,t} - \theta_{j,t}) \leq T_{ij}^{max}; \quad (\varphi_{ij,t}^{lmin}, \varphi_{ij,t}^{lmax}) \quad \forall (i,j) \in L, i < j, t \in H \tag{29}$$

In other words, the objective of the MO is to minimize the social cost (objective function of problem (22)), i.e. the cost of energy production minus the willingness of demand aggregators to pay for that energy. The decision variables of optimization problem (22) are:

- the power supply $g_{i,t}$ of each generator $i \in G$,
- the power consumption $d_{i,t}$ of each demand aggregator $i \in D$,
- the power supply/consumption $p_{i,t}^M$ of each DN $i \in V^M$ and,
- the voltage phase angles $\theta_{i,t}$ at all buses $i \in V^G$ at every timeslot t ($X_L = \{g_{i,t} | (i,t) \in G \times H, d_{i,t} | (i,t) \in D \times H, p_{i,t}^M | (i,t) \in V^M \times H, \theta_{i,t} | (i,t) \in V^G \times H\}$) .

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 (23) expresses the power balance at each bus *i* of the power grid. The dual variables of these constraints provide the LMPs. In (23), y_{ij} is the admittance of transmission line ij , $(i,j) \in L$. Equation (24) concerns the generators' minimum and maximum capacity. Furthermore, equations (25) and (26) express the constraints on the ramp up and down limits, denoted by RU_i and RD_i , respectively. Equation (27) refers to loads' upper ($d_{i,t}^{max}$) and lower bounds ($d_{i,t}^{min}$), while equation (29) constrains power flow to the transmission lines' *ij* capacity limits (T_{ij}^{max}). Additionally, constraint (28) enforces the 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 at each constraint (Eqs. (23)-(29)) following a semicolon. Finally, it is highlighted that the voltage phase angle of the reference bus is zero throughout the whole scheduling period ($\theta_{ref,t} = 0$).

6.4 Proposed algorithmic solution

ESP does not simply act as a price taker, but is able to anticipate the electricity market's reaction to its decisions (quantity/price bids). In order to model this process, a Stackelberg Game is formulated in which the ESP is the *Leader* and the electricity market is the *Follower*. The problem is solved from the ESP's point of view that acts strategically. Hence, an Optimization Problem constrained by an Optimization Problem (OPcOP) is formulated, in which the Upper Level Problem (Problem (21)) is constrained by the Lower Level Problem (Problem (22)):

$$\max \sum_{t \in H} \sum_{i \in V^G} \lambda_{i,t} \cdot p_{i,t}^M$$

$$\text{subject to } \begin{pmatrix} \text{Constraints (1)–(20)} \\ \text{Optimization Problem (22)} \end{pmatrix}$$

In the above bi-level optimization problem, the constraining lower-level problem (22) is a Linear Program and therefore, Slater's condition holds [71]. Thus, DC-OPF problem's Karush-Kuhn-Tucker (KKT) conditions are necessary and sufficient optimality conditions (satisfy convexity and constraint qualification). Thus, solving the following non-linear system of equations is equivalent to solving Problem (22):

$$-g_{i,t} + d_{i,t} - p_{i,t}^{M} + \sum_{j \neq \iota} y_{ij} \cdot \left(\theta_{i,t} - \theta_{j,t}\right) = 0 \qquad \forall i \in V^{G}, (i,j) \in L, t \in H \qquad (23)$$

$$c_{i,t}^{g} - \lambda_{i,t} - \varphi_{i}^{gmin,t} + \varphi_{i}^{gmax,t} - \varphi_{i}^{grd,t} + \varphi_{i}^{grd,t+1} + \varphi_{i}^{gru,t} - \varphi_{i}^{gru,t+1} = 0, \ \forall i \in G, t < T \quad (30)$$

$$c_{i,t}^{g} - \lambda_{i,t} - \varphi_{i}^{gmin,t} + \varphi_{i}^{gmax,t} - \varphi_{i}^{grd,t} + \varphi_{i}^{gru,t} = 0 \qquad \forall i \in G, t = T \qquad (31)$$

$$-c_{i,t}^{d} + \lambda_{i,t} - \varphi_{i,t}^{dmin} + \varphi_{i,t}^{dmax} = 0 \qquad \forall i \in D, t \in H \qquad (32)$$

$$c_{i,t}^{M} - \lambda_{i,t} - \varphi_{i,t}^{mmin} + \varphi_{i,t}^{mmax} = 0 \qquad \forall i \in V^{M}, t \in H \qquad (33)$$

$$\sum_{j \neq i,(i,j) \in L} y_{ij} \cdot \left(\lambda_{i,t} - \lambda_{j,t}\right) - \sum_{j > i} y_{ij} \cdot \left(\varphi_{ij,t}^{lmin} - \varphi_{ij,t}^{lmax}\right) + \sum_{j < i} y_{ji} \cdot \left(\varphi_{ji,t}^{lmin} - \varphi_{ji,t}^{lmax}\right) = 0 \quad \forall i \in V^{G}, t \in H \qquad (34)$$

$$0 \leq \varphi_{i,t}^{gmin} \perp g_{i,t} - g_{i}^{min} \geq 0 \qquad \forall i \in G, t \in H \qquad (35)$$

$$0 \leq \varphi_{i,t}^{gmax} \perp -g_{i,t} + g_{i}^{max} \geq 0 \qquad \forall i \in G, t \in H \qquad (36)$$

$$0 \leq \varphi_{i,t}^{grd} \perp g_{i,t} - g_{i,t-1} + RD_{i} \geq 0 \qquad \forall i \in G, t \in H \qquad (37)$$

$$0 \leq \varphi_{i,t}^{gru} \perp -g_{i,t} + g_{i,t-1} + RU_{i} \geq 0 \qquad \forall i \in G, t \in H \qquad (38)$$

$$0 \leq \varphi_{i,t}^{dmin} \perp d_{i,t} - d_{i,t}^{min} \geq 0 \qquad \forall i \in D, t \in H \qquad (39)$$

$$0 \leq \varphi_{i,t}^{dmax} \perp -d_{i,t} + d_{i,t}^{max} \geq 0 \qquad \forall i \in D, t \in H \qquad (40)$$

$$0 \leq \varphi_{i,t}^{mmin} \perp p_{i,t}^{M} + b_{i,t} \geq 0 \qquad \forall i \in V^{M}, t \in H \qquad (41)$$

$$0 \leq \varphi_{i,t}^{mmax} \perp -p_{i,t}^{M} + o_{i,t} \geq 0 \qquad \forall i \in V^{M}, t \in H \qquad (42)$$

$$0 \leq \varphi_{ij,t}^{lmin} \perp y_{ij} \cdot \left(\theta_{i,t} - \theta_{j,t}\right) + T_{ij}^{max} \geq 0 \quad \forall (i,j) \in L, i < j, t \in H. \quad (43)$$

$$0 \leq \varphi_{ij,t}^{lmax} \perp -y_{ij} \cdot \left(\theta_{i,t} - \theta_{j,t}\right) + T_{ij}^{max} \geq 0 \ \forall (i,j) \in L, i < j, t \in H \quad (44)$$

Equations (23) and (30) – (44) are the KKT conditions of Problem (22). Equation (23) represents the equality constraint of DC-OPF problem, while in Eqs (30) - (34) the partial derivatives of its Lagrangian function with respect to its primal variables are set to zero. Equations (35) – (44) express the complementarity conditions. We use the perpendicular symbol (⊥) to indicate complementarity, i.e. $0 \leq x \perp y \geq 0 \equiv \{x \geq 0, y \geq 0 \ x \cdot y = 0$.

Replacing the constraining optimization problem (22) with its KKT conditions in our OPcOP results in the following MPEC problem (45):

$$\min_{X_U \cup X_L \cup \Xi_L} -\sum_{t\in H}\sum_{i\in V^M} \lambda_{i,t} \cdot p_{i,t}^M$$

subject to Equations (1) – (20), (23), (30) – (44) (45)

Problem (45) is a single-level mixed integer non-linear optimization problem. The non-linearities are due to complementarity conditions (35) – (44) and its objective function. The optimization variables of problem (45) are: i) the set of the primal variables of upper level problem (denoted by vector X_U) which has been defined in section 6.3.5, ii) the set of the primal variables of the constraining lower level problem (denoted by vector X_L) which has been defined in section 6.3.6, and iii) set of the dual variables (denoted by vector Ξ_L) of the lower-level problem, where $\Xi_L = \{\lambda_{i,t},\ \varphi_{i,t}^{gmin}, \varphi_{i,t}^{gmax},\ \varphi_{i,t}^{grd}, \varphi_{i,t}^{gru}, \varphi_{i,t}^{dmin}, \varphi_{i,t}^{dmax}, \varphi_{i,t}^{mmin}, \varphi_{i,t}^{mmax},\ \varphi_{ij,t}^{lmin}, \varphi_{ij,t}^{lmax}\ |(i,t) \in\ V^M \times H,\ ((i,j),t)\ \in L \times H\}$. In order to tackle the non-linearities that come from complementarity conditions, we use the Fortuny-Amat & McCarl linearization technique [79]. Complementarity constraints of the type $0 \le x \perp y \ge 0$ can be replaced by the following set of linear constraints below:

$$0 \le x \le M \cdot u, \qquad 0 \le y \le M \cdot (1-u)$$

Constant *M* is large enough and *u* is an auxiliary binary variable. In our model, care is exercised to select a proper constant *M* to avoid numerical ill-conditioning. Therefore, Eqs. (35) – (44) are replaced by a set of linear constraints. For more details about these equations, the interested reader may refer to our paper in [72].

By using an ad-hoc linearization technique, the objective function of MPEC problem (45) is replaced by the expression:

$$-\sum_{t\in H}\sum_{i\in V^M}\left(c_{i,t}^M \cdot p_{i,t}^M\right) - \sum_{t\in H}\sum_{i\in V^M}\left(\varphi_{i,t}^{mmin} \cdot b_{i,t}\right) - \sum_{t\in H}\sum_{i\in V^M}\left(\varphi_{i,t}^{mmax} \cdot o_{i,t}\right).$$

Now, we make use of the Strong Duality Theorem for Problem (22), according to which the value of the primal objective function at the global optimal point is equal to the value of the dual objective function. As a result, problem (45) is finally formulated as follows:

$$\begin{aligned}\min_{X_U \cup X_L \cup \Xi_L \cup \Xi_B} & \sum_{t\in H}\sum_{i\in G}\left(c_{i,t}^g \cdot g_{i,t}\right) - \sum_{t\in H}\sum_{i\in D}\left(c_{i,t}^d \cdot d_{i,t}\right) - \sum_{i\in G}\sum_{t\in H}\left(\varphi_{i,t}^{gmin} \cdot g_i^{min}\right) \\ & + \sum_{i\in G}\sum_{t\in H}\left(\varphi_{i,t}^{gmax} \cdot g_i^{max}\right) + \sum_{i\in G}\sum_{t\in H}\left(\varphi_{i,t}^{grd} \cdot RD_i\right) + \sum_{i\in G}\sum_{t\in H}\left(\varphi_{i,t}^{gru} \cdot RU_i\right) \\ & - \sum_{i\in D}\sum_{t\in H}\left(\varphi_{i,t}^{dmin} \cdot d_{i,t}^{min}\right) + \sum_{i\in D}\sum_{t\in H}\left(\varphi_{i,t}^{dmax} \cdot d_{i,t}^{max}\right) \\ & + \sum_{i<j,(i,j)\in L}\sum_{t\in H}\left(T_{ij}^{max} \cdot \varphi_{ij,t}^{lmin}\right) + \sum_{i<j,(i,j)\in L}\sum_{t\in H}\left(T_{ij}^{max} \cdot \varphi_{ij,t}^{lmax}\right)\end{aligned}$$

Subject to Eqs. (1) – (20), (23), (30) – (34), (46)

We observe that the objective function of problem (46) is a sum of linear terms. Therefore, we have reformulated the initial OPcOP into a tractable Mixed Integer Linear Problem (MILP), which can be solved using a commercial MILP solver. The control variables of problem (46) are those of (45), with the addition of a set of auxiliary binary variables u. Again, for more details about this set of auxiliary variables, the interested reader may refer to our paper in [72].

6.5 Simulation setup and performance evaluation results

In order to demonstrate the performance of the proposed methodology, we consider two case studies as follows:

- **Case Study A:** a 6-bus illustrative example, in which the ESP controls a single DN, and
- **Case Study B:** the IEEE one-area reliability test system, in which the ESP practices spatio-temporal arbitrage controlling multiple DNs distributed among the transmission grid.

In both cases, we consider a 15-node radial distribution network [80] as shown in the system model figure in section 6.2 above. All simulation setup data can be found in FLEXGRID GitHub area[10]. A time horizon of T=24h is considered. Finally, the large constant M is chosen to be 2000 throughout the simulations.

6.5.1 Case Study A: 6-bus illustrative example

In this case study, we consider a 6-bus test system that is depicted in Figure 16, which is used to analyze the ESP's strategic bidding and scheduling of heterogeneous FlexAssets. Transmission lines, conventional generators and load data are taken from [81]. Bus 1 is considered to be the reference bus. As shown in the system model figure in section 6.2 above, a DN is located at bus 5. We assume that three solar PVs are located at nodes 2, 5 and 13 of DN and 3 wind turbines at nodes 8, 10 and 11. Renewable production data are derived from [82] and the power factors of every RG is set to 0.95. Additionally, inflexible loads are located at nodes 1, 2, 3, 4, 6, 7, 10, 11 and 12 and their consumption curves are based on load data from [80]. Figure 28 presents the total renewable energy production ($\sum_{n \in R_5} p^{rg}_{5,n,t}$) and inflexible load consumption curves ($\sum_{n \in I_5} p^{infl}_{5,n,t}$) as a function of time.

Furthermore, we assume that 4 ESSs of energy capacity 0.1667pu are located at nodes 5, 8, 10 and 13 of the DN. Their charge/discharge rate is 0.0833pu, their initial SoC is 0.0833pu and we set parameters $w_{5,s} = 1$, $\forall\, s \in S_5$. Also, without loss of generality, we assume lossless ESSs ($\eta^{d}_{5,s}$, $\eta^{c}_{5,s}$=1). Finally, we consider 6 shiftable loads located at nodes 4, 9, 10, 11, 13 and 14, which can consume from time $\alpha_{5,d}$ = 8h to time $\beta_{5,d}$= 18h, $\forall d \in F_5$. Their total energy consumption and their maximum power consumption per timeslot is 0.02667pu, while their power factor is 0.9. In order to demonstrate the advantages of the proposed system, three cases are presented:

- **Case 1:** ESP controlling a DN with renewable production, energy storage and flexible loads participates in day-ahead market as a price taker, considering DN physical constraints
- **Case 2:** ESP acts as a price maker but without considering the DN constraints (Eqs. (8) – (15))
- **Case 3**: ESP acts as a price maker considering DN constraints and implementing the proposed methodology.

[10] https://github.com/FlexGrid/FLEXGRID-UCS-2.4---EPSR-paper

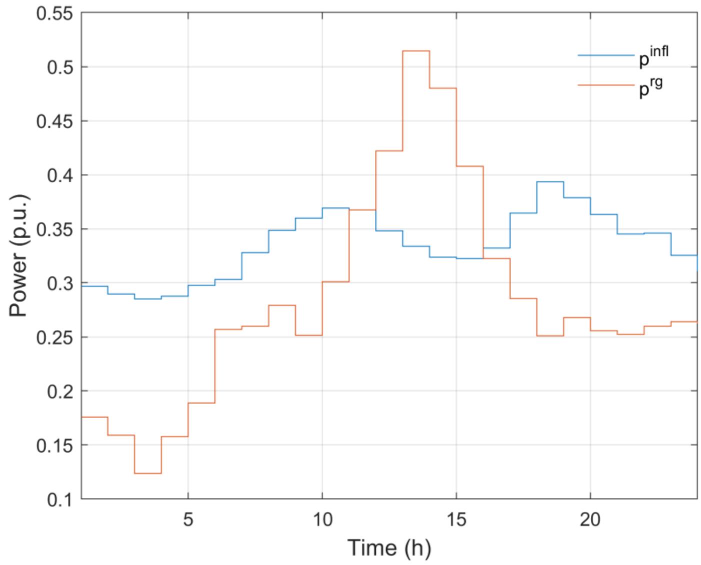


Figure 27: Renewable energy production and inflexible load consumption daily curves

6.5.1.1 Comparison between the three different cases

<u>Case 1:</u> In this case, the ESP is a non-strategic player in a perfect competition market. Thus, in order to calculate market equilibrium, a single-level optimization problem is solved (DC-OPF), in which MO maximizes social welfare. ESP makes a profit of 747.50€ from its participation in Day-Ahead electricity market as a price taker. Schedules of ESSs and shiftable loads are presented in the figure and table below.

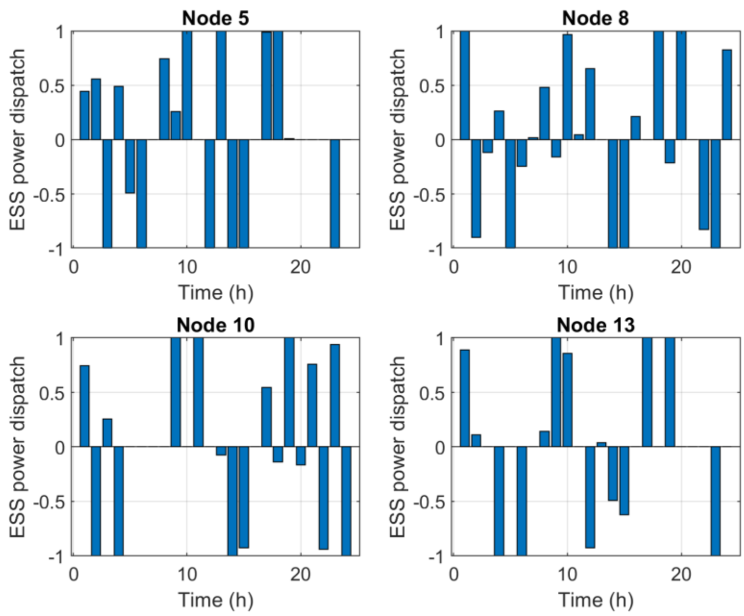


Figure 28: ESSs power dispatch schedules in Case 1 as a percentage of their maximum charge/discharge rates – Negative values indicate charging mode

Table 10: Power dispatch schedule of shiftable loads in Case 1 as a percentage of their total energy consumption

t / Node	8	9	10	11	12	13	14	15	16	17	18
4	0	0	0	0.384	0	0.616	0	0	0	0	0
9	0	0	0	0	0	1.000	0	0	0	0	0
10	0	0	0	0	0	1.000	0	0	0	0	0
11	0	0	0	0	0	1.00	0	0	0	0	0
13	0	0	0	0	0	1.00	0	0	0	0	0
14	0	0	0	0	0	1.00	0	0	0	0	0

Market results regarding LMPs at bus 5 and DN dispatch are presented in the figure below. We can conclude from Figure 29 and Table 10, that ESSs and shiftable loads are utilized to maximize social welfare, i.e. maximizing total utility of demand with the minimum production cost, while satisfying operational constraints. For instance, at time interval *t*=1, ESSs provide enough power, not only to satisfy DN's net load, but also to supply power to the grid in order for the System's Marginal Cost (SMC) to be low (SMC = 20€/MWh). If DN did not supply power to the grid, generators G1, G2 and G3 would satisfy the total demand load of the system, resulting in an SMC of 50€/MWh (i.e. price bid of G3). Furthermore, at time interval *t*=6, the ESSs in Nodes 5, 8 and 13 are charged in order for the DN to draw more power than is needed to satisfy its net load. This occurs because of the ramp down rates of generators G1 and G2, which cannot lower their production fast enough to match the total demand in that interval. The distribution network's power drawing creates more demand in order to absorb the excess production and prevent negative LMPs' occurrence. Another example of the utilization of DN's controllable assets towards social welfare maximization is the ESSs operation in timeslot *t*=17. In that time interval, the ESSs in nodes 5, 10 and 13 are discharged. Thus, DN supplies power to the grid reducing the generation cost by curtailing production power from G4 and decreasing the consumption curtailment (due to congestion in transmission line 4) of load in node 4. Flexible loads in this situation are mainly used to avoid voltage limit violations. Therefore, most of flexible load is chosen to operate in *t*=13 (only the 38.4% of shiftable load at node 4 consumes at a different timeslot, i.e. *t*=11), in which DN supplies power to the grid that mainly comes from the DN's net production (renewable production minus inflexible load).

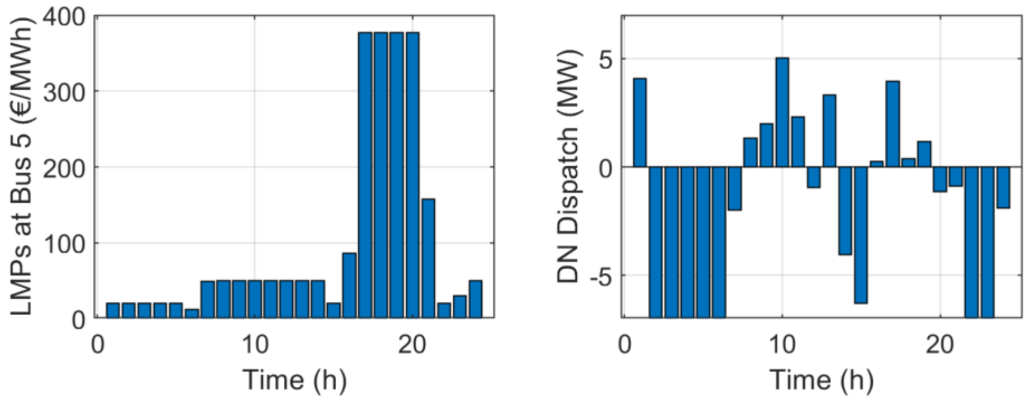


Figure 29: Market Results: LMPs at Bus 5 and Power Dispatch of DN in Case 1

<u>Case 2:</u> In this case, the ESP strategically bids in day-ahead electricity market but does not take into account distribution network constraints. Thus, ESP solves an MPEC problem in which Equations (8) – (15) are not included in the set of constraints of the upper-level problem. ESP schedules ESSs and shiftable loads with the objective to supply more power to the grid in times when LMPs are higher and draw power when LMPs are lower. In this way, voltage issues arise in areas that lie in the distribution grid's edges, at which RGs (nodes 10, 11 and 13) and loads (nodes 10, 11, 12, 13 and 14) are located. More specifically, voltage limit violations occur at node 10 during intervals *t*=11, 17 and 24, at node 11 during *t*=13, at node 12 during *t*=12, 13 and at nodes 13 and 14 during *t*=10, 11, 12 and 13. Moreover, active power flow limits are violated at several branches and timeslots. In order to maximize its profits from the participation in day-ahead market, the ESP decides to fully utilize DN's net production to supply power to the grid in times when LMPs are rising. This, however, results in power flows in the distribution network higher than the branches' capacity allows (see the two tables below for more details).

Table 11: Satisfaction (✓) or violation (✗) of nodal voltage limits in DN for each time instant in Case 2 (Case Study A)

Node / t	1	2	3	4	5	6	7	8	9	10	11	12	13	14
1	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
2	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
3	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
4	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
5	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
6	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
7	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
8	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
9	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
10	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✗	✗
11	✓	✓	✓	✓	✓	✓	✓	✓	✓	✗	✓	✓	✗	✗
12	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✗	✗	✗
13	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✗	✗	✗	✗
14	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
15	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
16	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
17	✓	✓	✓	✓	✓	✓	✓	✓	✓	✗	✓	✓	✓	✓
18	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
19	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
20	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
21	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
22	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
23	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
24	✓	✓	✓	✓	✓	✓	✓	✓	✓	✗	✓	✓	✓	✓

Table 12: Satisfaction (✓) or violation (✗) of active power flow limits for each branch of DN for each time instant in Case 2 (Case Study A)

Branch / t	1	2	3	4	5	6	7	8	9	10	11	12	13	14
1	✓	✓	✓	✓	✓	✓	✓	✗	✓	✓	✓	✓	✓	✓
2	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
3	✗	✗	✗	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
4	✓	✓	✗	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
5	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
6	✗	✗	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
7	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
8	✓	✓	✓	✓	✓	✓	✓	✗	✓	✓	✓	✓	✓	✓
9	✓	✓	✓	✓	✓	✓	✗	✗	✓	✓	✓	✓	✓	✓
10	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
11	✓	✓	✓	✓	✓	✓	✗	✗	✓	✓	✓	✓	✓	✓
12	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✗	✓	✓	✓
13	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
14	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
15	✗	✗	✗	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
16	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
17	✗	✗	✓	✓	✓	✗	✗	✗	✓	✓	✓	✓	✓	✓
18	✓	✓	✓	✓	✓	✓	✗	✗	✓	✓	✓	✓	✓	✓
19	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
20	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
21	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
22	✗	✗	✗	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
23	✓	✓	✗	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
24	✓	✓	✓	✓	✓	✗	✗	✗	✓	✓	✓	✓	✓	✓

Case 2 yields an apparent profit of 1700.3€ for the ESP. However, due to voltage and congestion issues, the ESP will have to perform corrective actions in near-real-time balancing market, with either very high monetary or societal (renewable energy curtailment/reduction in consumption of inflexible loads) costs. Thus, **Case 2 ultimately leads to more expensive or, even worse, technically infeasible schedules of ESSs and shiftable loads**.

Case 3: In this case, the ESP implements the proposed FLEXGRID methodology. Market outcomes in this case are presented in Figure 31, while ESSs' and shiftable loads' schedules are presented in Figure 32 and Table 13, respectively. ESP earns 897.33€, **which outperforms price taker solution (Case 1) by 20%**.

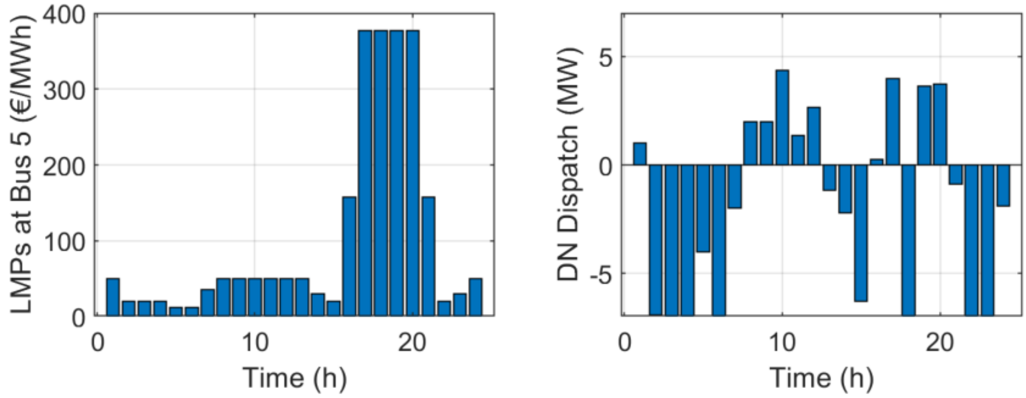


Figure 30: Market Results: LMPs at Bus 5 and Power Dispatch of DN in Case 3

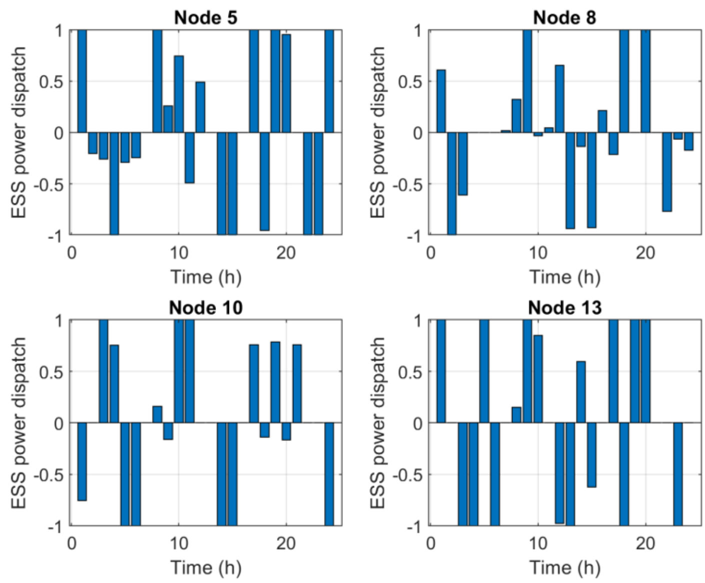


Figure 31: The ESSs power schedules (Case 3) as a percentage of their charge/discharge rates – Negative values indicate charging mode

Table 13: Power dispatch schedule of shiftable loads in Case 3 as a percentage (%) of their total energy capacity

t / Node	8	9	10	11	12	13	14	15	16	17	18
4	0	0	0	0	0	0	1.00	0	0	0	0
9	0	0	0	0	0	0	1.00	0	0	0	0
10	0	0	0	0	0	0	1.00	0	0	0	0
11	0	0	0	0	0	1.00	0	0	0	0	0
13	0	0	0	0	0	1.00	0	0	0	0	0
14	0	0	0	0.036	0	0.157	0.807	0	0	0	0

Studying Figure 31 and Figure 32, we note that, comparing to Case 1, the proposed methodology results in different LMPs at bus 5 in timeslots 1, 5, 7, 14 and 16. In particular, at *t*=1, ESP supplies 1MW at 50 €/MWh, discharging ESSs at nodes 5, 8 and 13. The total load is covered from G1, G2 and the DN, making DN the marginal supplier. At *t*=5, ESP purchases 4 MW at 12€/MWh, which is the lowest price bid that it can submit (cheapest generator's offer) in order to buy the necessary power amount to satisfy DN's inflexible loads and charge ESSs at nodes 5 and 10. Then, at *t*=7, ESP buys 2MW making a price bid at 36 €/MWh. LMP at bus 5 is determined by the cost of generating an extra MW by G3 (50 €/MWh) minus the value of dual variable concerning generator's G3 lower bounds ($\varphi_{6,t}^{gmin} = 14$ €/MWh). If ESP demanded more than 2MW, then G3 would be the marginal generator with $\varphi_{6,t}^{gmin}$ being 0 (according to complementarity condition (35)). In that case, LMP at bus 5 would be higher (50 €/MWh). Later, at *t*=14, ESP takes advantage of the generator's G3 ramp up limitation, and it purchases 2.22 MW at 30€/MWh in order to: a) complete the task of shiftable loads at nodes 4, 9, 10 and 14, and b) charge ESSs at nodes 5, 8 and 10. ESP's price bid sets LMP at bus 5 at 30€/MWh, since the cost of generating an extra 1 MW is 50€ (price bid of G3) minus 20€, which is the value of dual variable concerning ramp up constraint of G3 at t=15 (in case G3 generates 24.22MW at *t*=14, ramp up constraint of G3 will not be binding). At *t*=16, ESP takes advantage of the congested line 4 to make more profit by offering 0.25MW at 157.2368 €/MWh. ESS at node 10 supplies power 0.53 MW in order for ESP to satisfy DN's net demand (0.28MW) and sell 0.25MW in the market.

In general, we see that DN does not simply inject power to the grid at timeslots in which LMPs are higher due to congestion (i.e. $t \in [16, 21]$) or at timeslots during which its renewable production surpasses its load demand (i.e., $t \in [12, 15]$). This is due to distribution network physical constraints (voltage and power flow limits). For example, in *t*=13 we have the higher net production (5.4128 MW). At that time, ESP decides to run its shiftable loads at nodes 11, 13 and 14 in order to prevent nodal voltage amplitude rising above its upper limit (i.e. 1.05pu). In contrast, at *t*=14 and t=15 the excess production (4.6847 and 2.5669 MW, respectively) is used to charge ESSs and run shiftable loads. This happens in order to: a) keep voltage amplitude within the safe operation area (i.e., 0.95 – 1.05pu), and b) ensure that ESSs will be fully charged in order for the DN to sell power in the market at *t*=16 and *t*=17, when the price will be much higher.

6.5.1.2 Impact of heterogeneous FlexAssets' siting

RGs' Location: In addition to the simulation setup used in chapter 6.5.1.1, we investigate one more scenario of DN setup: we consider the same RGs as before, but located at different nodes of the DN. More specifically, wind turbines are located at nodes 3, 6 and 7, while solar PVs at nodes 2, 5 and 14. With this setup, if the ESP acts as price taker (Case 1), it enjoys a profit of 1162.7€. On the other hand, if the ESP acts as a price maker (Case 3) it earns 1413.1€, which is 21.54% higher than in Case 1. Higher profits are justified by the fact that in cases with high renewable production deep in the radial distribution network, ESSs are not fully utilized to maximize profits from energy temporal arbitrage, but they are partially operated to prevent network constraint violation. Hence, the siting of RGs can have a significant impact on ESP's profits.

ESSs' Location: In order to study the impact of ESSs' location on ESP's profits, we assume that 4 ESS (with the same technical characteristics as before) are located at nodes 2, 8, 9 and 14. ESP's profits are 1140.6€ in Case 1 and 1393.1€ in Case 3 (i.e., 22.13% higher if ESP implements the proposed FLEXGRID methodology, and 55.25% higher than the former DN setup). Furthermore, if we locate ESSs at nodes 4, 5, 6 and 10, then there will be no control on power injections from RGs in nodes 11 and 13 resulting in nodal voltage rising higher than 1.05pu, in which case problem (46) becomes infeasible. Thus, given the locations of RGs, ESSs, siting must be exercised carefully towards: a) the feasible operation of the DN, and b) the maximum possible profit from temporal arbitrage.

Shiftable Loads' Location: The relocation of shiftable loads from nodes 4, 9 and 10 to nodes 2, 5 and 12, respectively, will lead to profits of 766.44€ for a price taker ESP and 918.31€ for a price maker (i.e. 19.81% increase). We see that by relocating the shiftable loads, ESP increases its income by only 2.3%. However, if loads at nodes 11, 13 and 14 are moved and relocated elsewhere, then the problem becomes infeasible due to the upper bounds on the nodal voltage magnitude.

6.5.1.3 Impact of heterogeneous FlexAssets' sizing

We now study the impact of the aggregate size of renewable generation, storage capacity and flexible loads on the results. Initially, we consider a DN with the same storage capacity as in the former DN setup (4 ESS units at nodes 5, 8, 10 and 13), with a varying number of RG units and flexible loads (cf. figure below). Figure 23 depicts the ESP's financial balance (positive when ESP earns money from its participation in Day-Ahead Market (DAM) and negative when it experiences a trade deficit) in various cases regarding the number of RG units and shiftable loads. First, we observe, as expected, that the ESP's financial balance from the wholesale market participation increases with the number of RG units. Moreover, the proposed methodology (blue bars) always yields higher profit for the ESP than the price-taker solution (red bars) by a percentage varying from 2.59% (2 RG units and 6 shiftable loads) up to 94.10% (4 RG units and 6 flexible loads). Particularly, in some cases (4 RG units with 4 or 6 shiftable loads), Case 3 yields a positive balance, while Case 1 results in negative balance for the ESP. In the case that 6 RG units and 2 shiftable loads are located in the DN, then the problem is infeasible due to voltage violation for this specific ESS allocation.

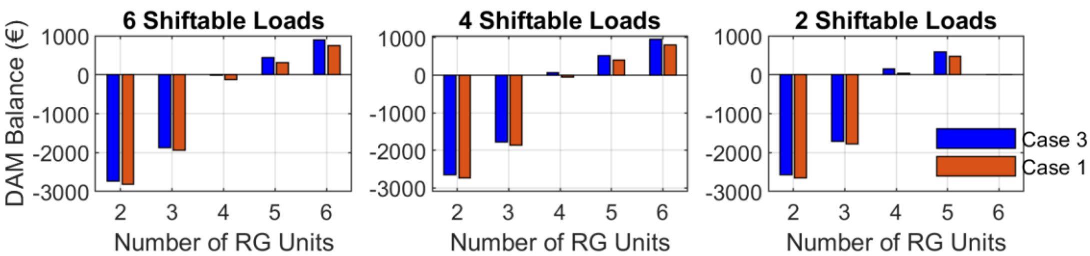


Figure 32: ESP's financial balance in Day-Ahead Market for different numbers of RG units and shiftable loads for a given number of ESS units

In addition, we consider another scenario where RES generation remains untouched (3 solar PVs at nodes 2, 5, 13 and 3 wind turbines at nodes 8, 10 and 11), while the number of ESS changes from 2 to 6 and shiftable loads can be 2, 4 or 6 (each one of both ESS units and shiftable loads have the same characteristic as in the former setup). As shown in Figure 34, increasing the number of ESS units results in larger profit for ESP in both Case 1 and 3. However, a price maker ESP earns more profit than a price taker ESP by 2.57-20.04%. In case of 2 shiftable loads, nodal voltage violation occurs, and the problem becomes infeasible.

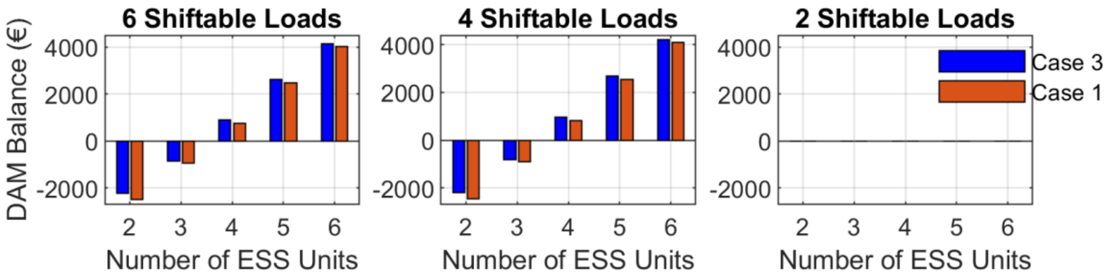


Figure 33: ESP's financial balance in Day-Ahead Market for different numbers of ESS units and shiftable loads for a given number of RG units

Finally, we study how the size of RES and storage capacity affects the financial balance of the ESP when 6 flexible loads are located in the DN. In Figure 35, we see that ESP's profits increase with the number of RG units. In case of 2 RG units, 6 ESS units are needed for Case 3 to yield a positive financial balance (in this case the price taker assumption still results in negative balance for ESP).

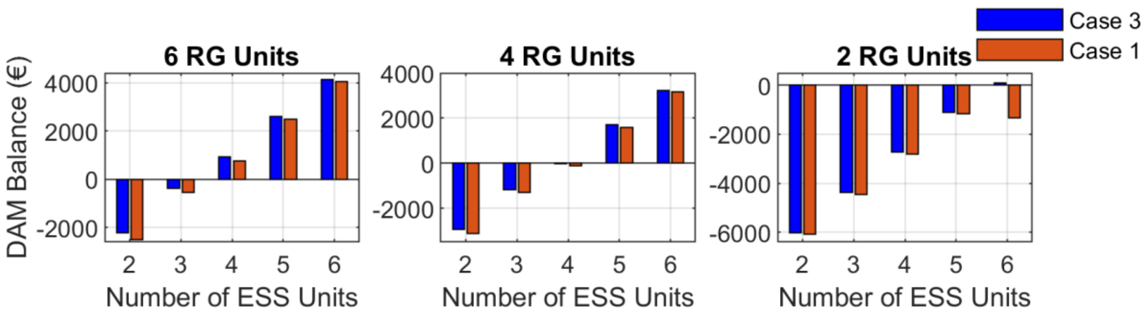


Figure 34: ESP's financial balance in Day-Ahead Market for different numbers of ESS units RG units for a given number of shiftable loads

6.5.2 Case Study B: IEEE one-area Reliability Test System

In this case study, we study an ESP coordinating geographically dispersed DNs in order to maximize its profits through employing spatio-temporal arbitrage. For this purpose, the IEEE One-Area Reliability Test System [83] is used, which is presented in Figure 36. Transmission lines, conventional generators and load data are taken from [84], while price bids of generators from [83][11]. The price bids of demand aggregators are the same as in Case Study A. Bus 13 is considered to be the system's slack bus.

Initially, it is assumed that ESP controls the heterogeneous FlexAssets of 3 different DNs (namely DN1, DN2 and DN3), which are located at buses 14, 15 and 23. The technical characteristics of the DN branches are the same as in the previous case study A, while DNs'

[11] For more details about the exact datasets that have been used, see our paper [72] and https://github.com/FlexGrid/FLEXGRID-UCS-2.4---EPSR-paper

assets data are presented in [72] . The resulting dispatches of DNs and LMPs at buses 14, 15 and 23 are presented in Figure 37 and Figure 38 below.

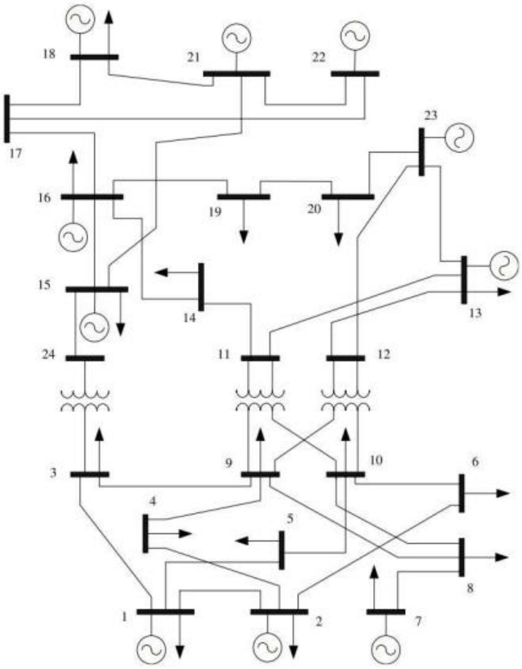


Figure 35: The IEEE One-Area Reliability Test System

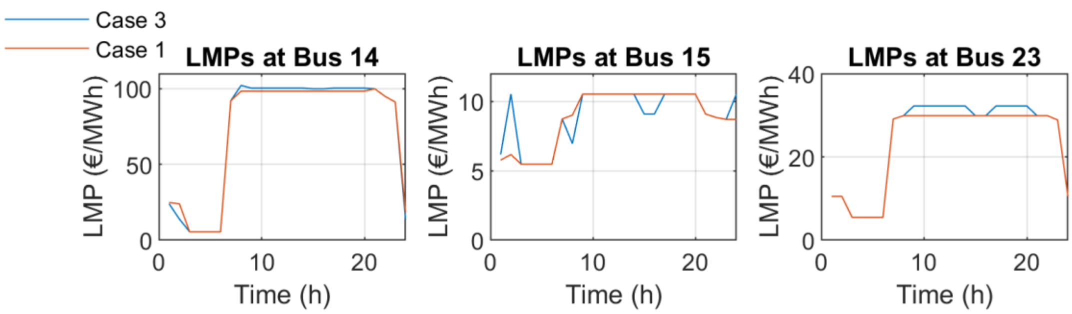


Figure 36: LMPs at Buses 14, 15 and 23

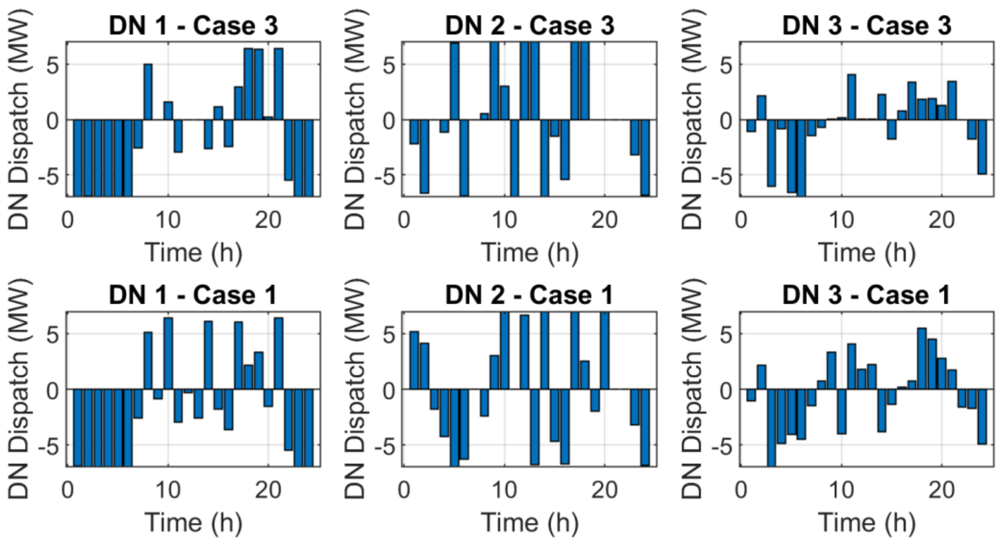


Figure 37: Power dispatch schedules of DN1, DN2 and DN3 in Cases 1 and 3

Figure 37 and Figure 38 present the impact of the strategic bidding and heterogeneous FlexAssets' scheduling of the ESP on LMPs and DNs' dispatch respectively. Strategic participation in day-ahead market decreases LMP at buses and timeslots in which DNs absorb power from the grid (e.g., Bus 15 at t=8, 15, 16). On the other hand, ESP increases its profits through strategic price bidding at buses and timeslots that DNs supply power to the grid (e.g., Bus 23 at t =17, 18, 19, 20). Additionally, in Figure 38, we can notice ESP exercising spatio-temporal arbitrage. For example, at t=2, DNs 1 and 2 buy power, while DN 3 sells power at day-ahead market. At t=5, DNs 1 and 3 draw power, while DN 2 supplies power to the grid. ESP also exercises arbitrage at timeslots 8, 11, 14, 15 and 16. ESP makes 456.64€ in Case 1 and 589.81€ in Case 3. Thus, ESP gains 29.16% more profit than Case 1 through the proposed methodology. Therefore, we conclude that, even if ESP possesses a very small portion of market's total generation (in each timeslot each DN can supply/draw to/from the grid 7MW of power, resulting in ESP possessing <1% of the total market generation and demand capacity) or consumption capacity, it can achieve significantly more profit if it acts as a price maker rather than a price taker.

6.6 Next research steps for M19-M26 period

As already mentioned, UCS 2.4 does not belong in the short list of UCS that will be integrated in FLEXGRID ATP at TRL 5. However, our next research step will be to apply the proposed mathematical model and algorithm for a MicroGrid Operator's (MGO) business case. The main difference will be that we will consider remote energy communities (or else energy islands), which experience weak grid connections. In this business case, maybe it is 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. Our goal for M19-M26 period is to adapt the existing mathematical model and algorithm and derive interesting performance evaluation results at TRL 3.

7 Independent large FlexAsset Owner leases storage for several purposes to several market stakeholders

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, a user may form new business strategies and lighten their financial burden. Rather than buying energy storage systems, the user 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.

> Within WP4 context, we develop mathematical model, the algorithm and conduct system-level simulations at TRL 3. The UCS 2.6 is not going to be integrated in the FLEXGRID ATP. The idea, functionalities and further proposals will be communicated through FLEXGRID's deliverables, scientific articles and other dissemination activities.

7.1 Problem statement, related state-of-the-art and FLEXGRID research contributions

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 [85]. 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. [86]. 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.

Within FLEXGRID project's context, in order to address the aforementioned issues, concept where **large FlexAsset owner leases storage** to several market stakeholders is proposed. Such approach should lower power market financial entry barrier and further motivate utilization of the energy storage systems.

Assuming market environment in which energy storage systems (with different power/capacity characteristics) are needed, various FlexAsset lease concepts are analysed and commented.

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. [87] 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 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

[88] 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 [89]. 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. [90] 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 [91]. 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 [92] 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 [93]. 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[12] 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[13] installs batteries on users' location but ordinates them in a centralized fashion.

The literature survey summary clearly shows that this topic has been researched by the scientific community. Nevertheless, the amount of published papers is rather small, and there is still a lot of room for improvement and future research. This use case will further enhance existing proposals and present new business models that are in line with FLEXGIRD's proposal of the distribution level flexibility market concept. Use cases from the industry (Green2store, Sonnenbaterie) present great motivation and confirmation to investment even greater effort in exploring this topic.

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.

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

[12] https://www.offis.de/offis/projekt/green2store.html
[13] https://sonnengroup.com/sonnenbatterie/

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 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 39, nicely illustrates how users may for different purposes have different storage needs.

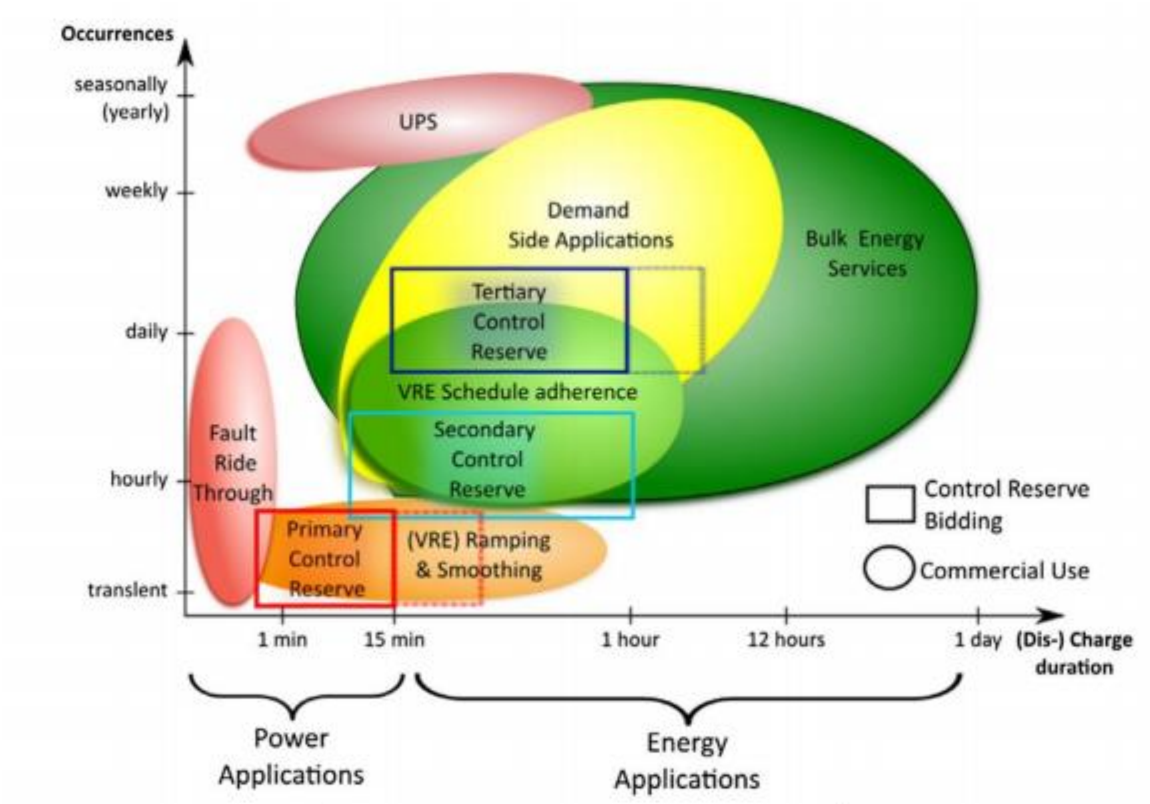


Figure 38: Average rate of occurrences and the typical charging/discharging duration [86]

The second concept is inspired by platforms such as Airbnb[14], Booking.com[15], Wolt[16], Bolt[17] (Food) and other similar services. Newly introduced entity, Storage Market Operator (SMO) plays the role of an intermediate (like the mentioned services), and it doesn't own any storage facilities. It presents a link between storage supply and demand. Furthermore, SMO guarantees both sides the compliance with the storage market rules. SMO aggregates the supply side capacity/power characteristics and the potential user has the opportunity to procure virtual storage system tailored to its needs. This approach should lower entry barriers, because capacity/power requirements for individual players willing to offer their

[14] https://www.airbnb.com/
[15] https://www.booking.com/
[16] https://wolt.com/en
[17] https://bolt.eu/

assets may have almost no minimum values. SMO's business model is highly dependent on the popularity of the platform as it may generate profit from subscription packages and/or fees from conducted transactions. There is also possibility that SMO is a non-profit regulatory body, but in the scope of this research problem, the tendency is toward the profit-oriented option just like Airbnb and similar operators.

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, both in this and following deliverable (D4.3). 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 Algorithmic solution

Modern commercial solvers are still unable to deal with the bilevel problems. Hence, such problem needs to be reformulated as a single level problem. This will be done using Karush-Kuhn-Tucker (KKT) conditions. The resulting problem will be a Mathematical Program with Equilibrium Constraints (MPEC). Should some non-linearities occur, appropriate linearization approaches will be utilized (e.g. Big-M approach). Detailed algorithmic solution will follow in the D4.3.

7.5 Simulation setup and performance evaluation results

The inputs needed for the purpose of this use case scenario are:

- Energy storage systems technical data
- Prices of different energy storage systems technologies
- Network topology
- Market prices
- Hourly demand
- Hourly supply

The relevant KPIs for this use case scenario:

- RES curtailment
- Large FlexAsset owner profit
- Balancing costs
- Peak shaving (compared to the BaU)
- Change of the energy storage capacity in the system
- Congestion occurrence frequency
- Prosumers electrical bills (cost reduction)

7.6 Next steps

Within M19-M26, we will elaborate on the UCS 2.6 work in order to further develop both of the proposed concepts. Regarding the first concept, the emphasis will be on formulating comprehensive bilevel problem, which will then be reformulated as MPEC (and linearized if necessary) to solve it in commercially available solvers. Whereas, for the purposes of the second concept, peer-to-peer trading and respective platform will be further analysed and appropriate solutions proposed. To validate formulated models, system-level simulations will be conducted, considering different possible scenarios. Hence, multiple case studies (e.g. different market prices) will be tested. To conclude, or goal in the following period (M19-M26) is to finish the mathematical model and algorithm, validate it, publish and comment acquired results.

8 S/W integration in FST and FLEXGRID ATP

8.1 Summary of FST and related S/W architecture

The FlexSupplier's Toolkit (FST) has been designed in such a manner so it may be commercially exploitable as a standalone S/W toolkit, which can be integrated as a S/W "plug-in" in other larger S/W platforms used by the interested ESPs. In the scope of the FLEXGRID project, FST will be integrated in the FLEXGRID ATP platform. Its functionalities will be extensively tested throughout lab experiments and pilot tests as part of FLEXGRID's WP6 and WP7 work.

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

- Research done until now within WP4, with emphasis on algorithms described in chapters 3-5, presents first version of the FST's functionalities. As primary use cases 2.1, 2.2 and 2.3 will be running at the FST's backend, their initial results are extensively tested and analyzed.
- FST's modelling work has been defined and provided in D6.1 (M18). More precisely for each of the three main algorithms to be integrated in FST (UCSs 2.1, 2.2. and 2.3), APIs for the interconnection between the: i) FST's backend services, ii) FST's frontend services and iii) central FLEXGRID database have been designed.
- D8.2. (M18) provides Key Exploitable Results (KERs) identified for the FST's case. Furthermore, it has been explained how the proposed FST's functionalities may potentially benefit profit oriented ESP.

Future work, from M19 onwards, will consist of continued WP4 research work and integration of the first versions of the algorithmic solutions in the FST (starting with UCS 2.3). All of the selected algorithms will be extensively tested, analysed and validated in the FLEXGRID ATP at TRL 5. The progress of FST's development throughout the whole project's lifetime is illustratively shown in the figure 28:

- The basis of the WP4 work is a high-quality scientific research work resulting in advanced mathematical models and algorithms beyond state-of-the-art. This work is then published in high-quality scientific journals and conferences (TRL 3)
- The deployment of RESTful Application Programming Interface (REST API) servers and REST API client for the integration of FST's frontend and backend services for the respective algorithms follows the extensive testing and validation at TRL 3.
- The Following stage consists of testing and validation of the FST algorithms via the use of FLEXGRID ATP at TRL 5 (WP6)
- The whole process is concluded with small-scale real-life pilot tests of the FST's functionalities (TRL 6).

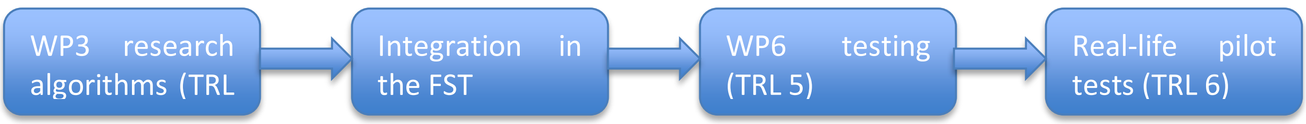


Figure 39: FST development timeline

8.2 FST's frontend services

The ESP user may use a variety of dedicated services from the FLEXGRID ATP. The log-in process to the ATP platform is conducted via a single sign-in authentication process and then the ESP user is redirected to the FST's frontend services. The Graphical User Interfaces (GUIs) will be based on the existing WISECOOP application developed under the H2020 WISEGRID project. The goal of FLEXGRID is to use WISECOOP as a S/W substrate based on which the FLEXGRID's WP4 algorithms will be integrated.

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

- **ESP's OPEX minimization**
- **ESP's CAPEX minimization**
- **ESP's profit maximization**

"OPEX minimization" functionality 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 user should gain insight what could potentially lower/increase OPEX if changed by observing visualizations shown by the FST service. Two modes of operation are considered:

- <u>Online operation:</u> 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.
- <u>Offline operation:</u> The ESP user runs various "what-if" simulation scenarios assuming various FlexRequests and FlexAsset portfolios.

On the other hand, **"CAPEX minimization"** service deals with the optimal sizing and siting of the potential new FlexAssets in a least capital cost manner while meeting some goal such as e.g. 5% OPEX reduction. Thus, the model takes into account network topology, at least the minimum of needed information for the optimal siting and sizing algorithm to successfully run. The ESP user should visualize its total investment costs with respect to the given objective. As online operation doesn't make much sense for the respective use case, only one operation mode is considered:

- <u>Offline operation:</u> 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" functionality provides the ESP an optimal FlexOffer for simultaneous participation in multiple markets to maximize its business profits. The idea is to show that simultaneously participating in more markets may yield greater profit for the interested party. The user shall visualize its business profits by simultaneously participating in a different combination of markets. Two modes of operation are considered:

- <u>Online operation:</u> 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 FlexOffers to submit in ATP.
- <u>Offline operation:</u> 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.

8.3 FST's backend services and integration in FLEXGRID ATP

Following up the FST's frontend services, three main algorithms will be implemented in the FST's backend, namely:

- An optimal scheduling algorithm that optimally schedules the observed FlexAssets to reduce OPEX and respond to the issued FlexRequest. The proposed solution is described in chapter 3 (cf. UCS 2.1)
- An optimal siting and sizing algorithm, that produces an optimal investment plan to meet a given desired objective knowing the relevant network topology data. The proposed solution is described in the chapter 4 (cf. UCS 2.2)
- Bi-level algorithm, that co-optimizes ESP's participation in several energy and local flexibility markets to maximize user's profit. The proposed solution is described in chapter 5 (cf. UCS 2.3)

The detailed data model (i.e. algorithmic inputs and outputs) is presented in chapter 4 of D6.1 for each of the algorithms listed above. Once the ESP user logs in to the FLEXGRID ATP platform and gets redirected to the FST module, three tabs (on for each of the algorithms listed above) will be visible. After clicking one of them, the ESP user will have the opportunity to configure/customize/fill in the input parameters that are needed for each respective algorithm to run. Step 1 process, shown in the figure below, starts after the user clicks on the "Run algorithm" button. In a more precise manner, the API client that resides at the FST frontend will automatically gather all the input parameters and send them to the API server that resides at the FST backend.

After the FST backend receives the input parameters, it follows the request for the required input data from the FLEXGRID central database (DB). An API client that resides at FST backend requests for the input data from an API server residing at the central DB. In the step 3, the input data is retrieved, so the algorithm can be executed.

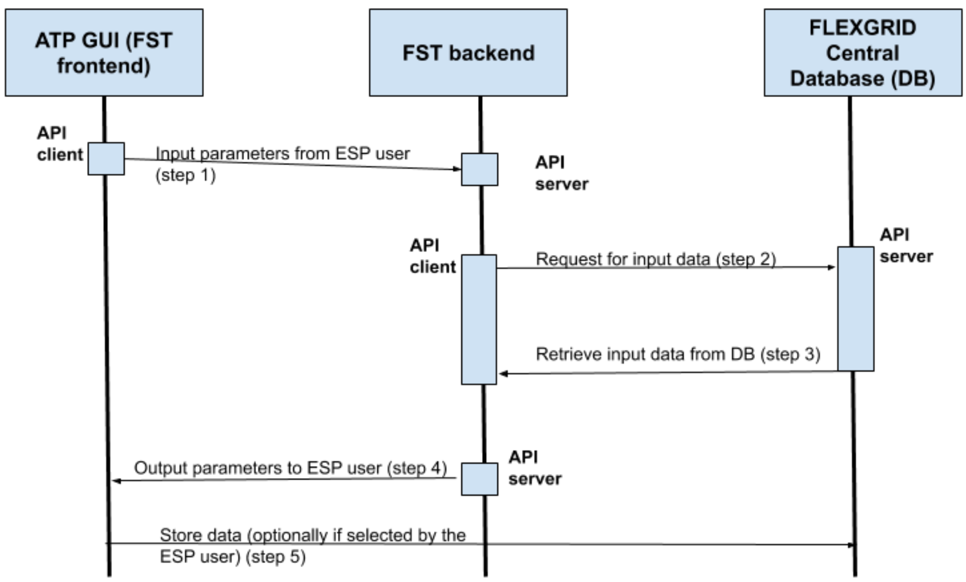


Figure 40: Sequence diagram for the S/W integration of WP4 research algorithms in FST and FLEXGRID ATP

After the algorithm produces the results, the output will be automatically gathered by the FST-ATP API and sent to the FST frontend. In that manner, the ESP user may visualize the results in a comprehensive and user-friendly manner. Step 5 is the final step of the process. It provides the ESP user an opportunity to understand the results and, optionally, to store them in the central DB for further elaboration. In that way, the user may retrieve, visualize and compare them with other results in the future.

9 Conclusions and next steps

In the following months, WP4 partners will progress the current research work presented in this report and will provide the final research results in Month 26.

Regarding market prices and the PV prediction problem, UCY will follow the research plan described in sections 2.1.6 and 2.2.6, respectively. As of UCS 2.3 and 2.4 work, ICCS will follow the research plan described in sections 5.6 and 6.6, respectively. While UNIZG, for the UCSs 2.1, 2.2 and 2.6 described its future research plan in the sections 3.6, 4.6 and 7.6, respectively.

In the figure below, the timeline schedule of WP4 is illustrated. Milestone #5 has been achieved with this deliverable, while one more milestone remains to be accomplished for month #26 with the submission of D4.3.

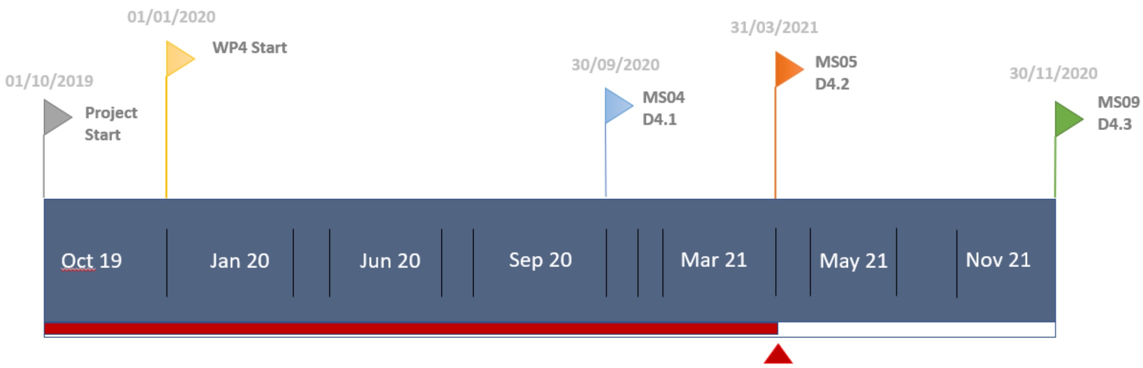


Figure 41: Timeline schedule of the WP4 work

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