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

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Objectives and challenges towards advanced ESP and RESP BMs

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Glossary of Acronyms

Acronym	Definition
AFAT	Automated Flexibility Aggregation Toolkit
AIS	Elevation Angle
ANN	Artificial Neural Network
ARIMA	Autoregressive Integrated Moving Average
ARMA	Autoregressive Moving Average
AzS	Azimuth Angle
BM	Balancing Market
BP	Back-Propagation
BRNN	Bayesian Regularization Neural Network
BRP	Balance Responsible Party
BSP	Balancing Service Provider
BSU	Battery Storage Unit
CAGR	Compound Annual Growth Rate
CAPEX	Capital Expenditure
CES	Cloud Energy Storage
CREC	California Renewable Energy Collaborative
DA	Day-ahead
DA-DLFM	Day-Ahead Distribution Level Flexibility Market
DA-EM	Day-Ahead Energy Market
DA-RM	Day-Ahead Reserve Market
DC	Direct Current
DER	Distributed Energy Resource
DLFM	Distribution Level Flexibility Market
DN	Distribution Network
DR	Demand Response
DSM	Demand Side Management
DSO	Distribution System Operator
ELM	Extreme Learning Machine
ESP	Energy Service Provider
ESS	Energy Storage System
EV	Electric Vehicle
FMO	Flexibility Market Operator
FST	FlexSupplier's Toolkit
GenCo	Generator Company
GHI	Global Horizontal Irradiance
GUI	Graphical User Interface

HLUC	High-Level Use Case
HVAC	Heating, Ventilation and Air-Conditioning
IEA	International Energy Agency
IGDT	Information Gap Decision Theory
KKT	Karush-Kuhn-Tucker
KPI	Key Performance Indicator
LL	Lower Level
LMP	Locational Marginal Price
LSE	Load Serving Entity
LS-SVM	Least-Squares Support Vector Machine
MAE	Mean Absolute Error
MAPE	Mean Absolute Percentage Error
MG	MicroGrid
MILP	Mixed-Integer Linear Programming
MO	Market Operator
MOE	Merit Order Effect
MPEC	Mathematical Program with Equilibrium Constraints
MRA	Multi-Resolution Analysis
NID	Network Interface Diagram
nRMSE	Normalized RMSE
NWP	Numerical Weather Prediction
OPcOP	Optimization Problem constrained by an Optimization problem
OPEX	Operational Expenditure
OPF	Optimal Power Flow
P2P	Peer-To-Peer
PV	Photovoltaic
PVPS	Photovoltaic Power System
RES	Renewable Energy Sources
RG	Renewable Generator
RMSE	Root Mean Square Error
ROI	Return-on-Investment
RPCF	RES Production Curve Forecasters
RPCFAL	RES Production Curve Forecast Accuracy Levels
S/W	Software
SLFN	Single Hidden Layer Feedforward Neural Network
SMO	Storage Market Operator
SoC	State-of-Charge
SOCP	Second-Order Cone Problem
SOE	State-of-Energy
SOM	Self-Organizing Map
SVM	Support Vector Machine
SW	Social Welfare
TN	Transmission Network

TRL	Technology Readiness Level
TSO	Transmission System Operator
UCS	Use Case Scenario
UL	Upper Level
VESS	Virtual Energy Storage System
VPP	Virtual Power Plant
VRE	Variable Renewable Energy

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Document History

Table 1: Document History Summary

Revision Date	File version	Summary of Changes
01/07/2020	v0.1	Draft ToC circulated within the entire consortium.
25/07/2020	v0.3	1st round of contributions from all involved partners gathered
01/09/2020	v0.4	Integrated 1st version and circulated among partners
07/09/2020	v0.5	1st internal review comments
21/09/2020	v0.6	All partners provided their 2nd round of contributions and the integrated 2nd version was circulated among partners
25/09/2020	v0.7	DTU reviewed the pre-final version and provided comments for changes/enhancements.
29/09/2020	v0.9	All partners have addressed the comments from the internal review process and UNIZG-FER provided the final version to the Project Coordinator
30/09/2020	v1.0	Coordinator (ICCS) made final enhancements/changes and submitted to ECAS portal

Executive Summary

This report is the official deliverable of H2020-GA-863876 FLEXGRID project. The deliverable is primarily concerned with the research work done as part of the FLEXGRID's Work Package (WP) 4. The main subject of interest in this WP is the Energy Service Provider (ESP) actor[1]. In such manner, research is oriented towards 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. Research objectives, and consequently results, are manifold: i) the development of MPEC/EPEC algorithms (appropriate for planning and operating ESP's assets), ii) the development of advanced forecaster of RES generation and market trends (also part in WP3), iii) ESS sharing management and auction algorithms, iv) the factorization of: a) Co-optimization of ESS and DSM, b) stacked revenue models, c) market affection, d) underlying network cost and constraints and v) the development of policy automation algorithms. Specifically, this deliverable deals with the following aspects for each one of the research problems under the WP4 scope:

- Research motivation and novel FLEXGRID contributions
- Survey on related works in the international literature
- Basic system model to be followed per research problem
- Basic problem formulation and algorithmic solutions
- Dataset to be used for simulation setup and most important KPIs

The deliverable D4.1 due in month 12 of the project is the first out of three deliverables (D4.2 in month 18 and D4.3 in month 26) concerning the progress in WP4. Therefore, D4.1 is intended as an extensive introduction to all fundamental factors defining the core of each research problem in chapters 2-7 respectively. In such manner, the description of each research problem includes current state-of-the-art survey. Moreover, as the list above suggests, chapters introduce explanation of the basic system models and problem formulations complemented with the draft versions of the algorithmic solutions to be implemented within the next months. As the final result highly depends both on the availability of the required input data and key performance indicators that indicate model performance, each chapter dedicated part of the description to those topics, too.

Chapter 2 deals with the PV generation forecasting models and market price forecasting models. Both topics are introduced following the subchapters as listed above. Work done within the scope of chapter 2 shall be used as input in other WP4 research problems, but also it is an essential part of the WP3 research work.

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[1] By the term "ESP", we mean the market actor who owns and operates several types of FlexAssets such as storage and demand side management units. The main difference with the independent flexibility aggregator (cf. FLEXGRID D3.1 w.r.t. to WP3 research work) that we use in FLEXGRID is that the independent aggregator aggregates distributed flexibility from numerous small-scale end energy prosumers and thus does not own any FlexAssets like the ESP.

Chapter 3 describes a business model, where the main goal of the objective function is to minimize ESP's Operational Expenditures (OPEX) by optimally scheduling the consumption of end users, production of RES and storage assets. The main aspects of the problem are listed (i.e. battery modelling, scenario quality and demand response schemes) and a single level problem formulation is stated, in addition to the needed dataset, KPIs and international literature review.

On the other hand, chapter 4 considers how ESP can minimize Capital Expenditures (CAPEX) by making optimal investments on RES and FlexAssets. The formulation is a network-aware single level problem. CAPEX is also dependent on day-to-day operation strategies, so various OPEX models are included too.

Chapter 5 demonstrates basic model, problem formulation and algorithmic solutions where it is investigated how ESP can maximize its profit by co-optimizing its participation in several wholesale energy and local flexibility markets. In that manner, in this Use Case Scenario (UCS), FLEXGRID proposes a novel energy market architecture, in which the day-ahead distribution level flexibility market (DA-DLFM) follows the market clearing process of the distribution network-unaware day-ahead energy and reserve markets without changing the existing wholesale energy market structure. Furthermore, a bi-level formulation is proposed, where the profit maximization is the upper level problem, while two lower level problems are considering day-ahead reserve market (DA-RM) and DA-DLFM clearing process respectively. In addition, it is explained how Karush-Kuhn-Tucker (KKT) conditions are utilized to transform the problem to a Mathematical Problem with Equilibrium Constraints (MPEC).

Chapter's 6 most important contribution is its proposed business model that simultaneously: i) offers to a price maker ESP entity the capability to optimally bid in an imperfect day-ahead electricity market, ii) allows the adjustment and the respect of operational limits of a physical distribution network, and iii) orchestrates a virtual and heterogenous flexibility portfolio. The problem has a bi-level structure, thus the methodology to convert it into a formulation that is convenient for the commercial solvers is explained. Moreover, proposed simulations are intended to test the algorithmic solutions in different scenarios and compare them to the current state-of-the-art.

The research problem described in chapter 7 presents somewhat an abstract business model, where large FlexAsset Owners may lease the storage for several purposes to several market stakeholders. In addition to the lease model, a business platform similar to Uber, Booking, etc. is also proposed. In this constellation, a flexibility market operator runs a platform where subjects that want to procure the FlexAssets and FlexAsset owners match their bids and offers. The formulation of the first variant is a bi-level problem, where the upper level deals with the large FlexAsset owner investment problem, while the lower level problem considers other players. When it comes to the latter model, it is based upon a peer-to-peer business model and the algorithmic solution will deal with price forming possibilities and matching the ones offering the service with others wanting it.

In the following months, FLEXGRID consortium will further work on the models presented in this deliverable. Consequently, this should result with the implementation of the presented modules as part of the FlexSupplier's Tookit (FST). Hence, in Chapter 8, the operation of the proposed FST and how the algorithms presented in chapters 2-5 will be integrated in the toolkit are examined. A high-level abstraction of the Graphical User Interface (GUI) of an ESP user is described, where the main visualizations within the ATP are stated.

1 Introduction

FLEXGRID project aims at facilitating energy sector stakeholders (i.e. DSOs, TSOs, ESPs and RESPs) to successfully respond to the challenges posed by a paradigm shift in the modern power industry. Moreover, by proposing novel business models, it creates prerequisites even to enhance and upgrade the modern power systems with high RES penetration. Different work packages tackle the matter from different perspectives and the idea is to integrate all of the developed submodules into one integrated platform that can then accommodate the needs of various stakeholders according to their roles in the energy sector.

Focus of the WP4 is the Energy Service Provider (ESP). ESP is a general term used in the FLEXGRID project meaning a profit-oriented company, which may make contractual arrangements with various types of flexibility assets. In order to prepare the role of an ESP in the modern power system paradigm with high RES share, DERs, prosumers (opposed to passive consumers) and the associated problems (e.g. congestion) that the ongoing transition brings, WP4 use case scenarios are tackling the problems and creating opportunities for developing novel business models and strategies. Throughout the chapters 2-7, a detailed survey of current state-of-the-art situation is given for each respective research problem. According to the current state, it is explained how work done as part of the WP4 (and part of the FLEXGRID project in general) further improves current state-of-the-art solutions. Furthermore, a basic system model complemented with a basic problem formulation and algorithmic solution give a glimpse to the interested reader of what is currently being developed and what is the predicted end result for each of the respective use case scenarios (UCS). Each of the chapters (2-7) is concluded with a tentative list of used datasets and most important KPIs to precisely measure what impact research done in the scope of this WP really has.

Just by looking at the research topics names, one might notice similarity between some of them, but also complementarity and diversity in general. The idea is that the proposed solutions accommodate the needs of ESPs with different potential needs and constraints. In order to easily navigate between different options that are available to the ESP user, developed modules (algorithmic solutions) will be part of the FlexSupplier’s Toolkit (FST), which is then part of the FLEXGRID ATP platform. The FST GUI (frontend services) will be developed by ETRA partner, while backend intelligence of FST will be integrated by UNIZG, ICCS and UCY. Integrating all of the submodules developed in WPs of this project, the result shall be holistic and novel business strategies and solutions for interested stakeholders in the ongoing power systems transition.

The deliverable D4.1 focuses on the above mentioned segments, it describes each one of the six use case scenarios in great detail concerning the work to be done, while further background of the use cases along with the definitions of the newly introduced roles, market structure and FLEXGRID platform in general may be found in already published deliverables D2.1 and D2.2.

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 Research motivation and novel FLEXGRID contributions

Over the past decade, the energy industry has been undergoing a major reconstruction process. The integration and development of renewable energy sources (RES) in the power grid is rapidly growing, while demand and prices are becoming more unstable and less predictable than ever. Additionally, the stability of the power grid faces new challenges due to variable and intermittent nature of generated power that is dependent on the weather conditions [1]. An important feature for producers and plant operators is an accurate PV power forecasting tool that can mitigate the adverse power quality impacts that are posed by the abovementioned high shares of distributed PV systems that increase the generation capacity ("ramp rates") and lead to grid instability [2], [3].

For successful integration of high levels of solar energy production, an accurate PV generation forecast is required. PV generation forecasting is becoming increasingly important as solar penetration in the electric grid increases [4]. Therefore, accurate knowledge of PV system characteristics and behaviour must be available to have an accurate PV power forecasting model [5]. The importance of accurate PV output forecast is beneficial both to system operators and consumers, since it minimizes the costs and uncertainties. Furthermore, PV plant managers avoid possible penalties that will be incurred due to deviations between the forecasted and the produced energy. Regarding this, the accurate PV power forecasting can mitigate the power quality effects that are posed by large shares of distributed systems through active grid management. As a result, this can assist utilities and plant operators in energy management and dispatchability planning.

The short-term, intra-hour PV generation forecasts are suitable for control operations (power ramping and voltage flicker predictions), while the mid-term PV generation forecasts, intra-day and day-ahead (DA), are important for grid operators, who control different load zones or trade outside of their area [6]. Furthermore, for the prediction of the power output of a grid-connected PV systems machine learning model based on Artificial Neural Network (ANN) can be used. ANNs are powerful machine learning algorithms that are very popular and proven for prediction and classification. ANNs are very efficient for training as they are capable of reflecting the information of new instances on a model very efficiently.

Additionally, ESPs/aggregators will be provided with these forecasting services. The novel FLEXGRID contribution services will include accurate PV generation forecasting to

ESPs/aggregators by aggregating their end-users PV generation and also considering the other available assets such as battery storage. FLEXGRID's forecasting services will be located in the Automated Flexibility Aggregation Toolkit (AFAT) and FlexSupplier's Toolkit (FST).

2.1.2 Survey on related works in the international literature

PV power forecasting is recognized as the most important and cost-effective tool necessary to enable higher PV energy shares at distribution feeders since it affects a range of system operations including load dispatch, scheduling and real-time balancing.

The PV energy forecasting generally depends on the time horizon and resolution of the forecast, the availability of the data and the particular forecasted outputs [7]. Different data sources used for PV power forecasting such as ground measurements, numerical weather predictions (NWPs), satellite data or sky images. The most used data source for the short-term (up to 6 hours) PV power forecasting are the measured PV outputs and weather data, because the model can distinguish the behaviour of the PV system easily, thus avoiding the error from the NWPs. The NWPs datasets are commonly used for PV power forecasts extending 6 hours ahead. For the day-ahead (DA) PV production forecasting, NWP outputs are required. More specifically, to classify the weather type and to enhance the "training set" of a constructed ANN, a Self-Organizing Map (SOM) is designed to achieve precise forecast with a mean absolute error (MAPE) of 6.36 % [8].

Furthermore, the most common approach for the DA PV power forecasting focused on the development of physical and semi-empirical models. This is not an easy task, as specific information of the reference PV systems is necessary (latitude, longitude, installed capacity, technical characteristic and electrical configuration) [9].

Task 13 of the International Energy Agency (IEA) Photovoltaic Power System (PVPS) is considered to be a state-of-the-art study on solar forecasting [10]. Task 13 showed 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 [10]. This study also showed that PV power forecast is also dependent on the location. Moreover, the California Renewable Energy Collaborative (CREC) study, showed that accurate forecast with a root mean square error (RMSE) of 6 % can be obtained with clear sky conditions. For the remaining conditions, all the analyzed forecasts from different providers exhibited RMSE of at least 20 %, but as large as 40-80 % were also observed [11].

2.1.3 Basic system model to be followed

To provide accurate short-term and long-term Renewable Energy Sources (RES) production forecast, a basic system model should be followed based on a non-parametric ANN model, which is optimized according to the selection of the input and output parameters that are used for the training. The advantages of ANNs compared to other approaches is their adaptability and learning ability [12].

The three phases that are followed in order to have an accurate short-term and long-term RES production are called: i) training (to effectively apply a learning technique to a performance function), ii) validation (to identify the important features and architectural parameters of each model) and iii) testing (to assess the prediction accuracy performance). More specifically, a sequence of the training and validation set must be performed by varying the input parameters, the duration of the training and the architectural parameters of the devised models in order to capture the systematic behaviour of a PV system.

The employed model utilizes a back-propagation (BP) algorithm to minimize the error. The BP algorithm during the "training set" calculates the contribution error of each neuron of the ANN model after a batch of data, by distributing the error back from the output through the network layers. The ANN model is principally a Bayesian Regularization Neural Network (BRNN) in which a Bayesian Regularization and BP algorithm are applied during the "training set" and "validation set".

The BRNN initially uses the input values and multiplies them with a set of weights to be able to produce linear combinations, and then transform them using a non-linear function to produce values of the state of the neurons in the hidden layers.

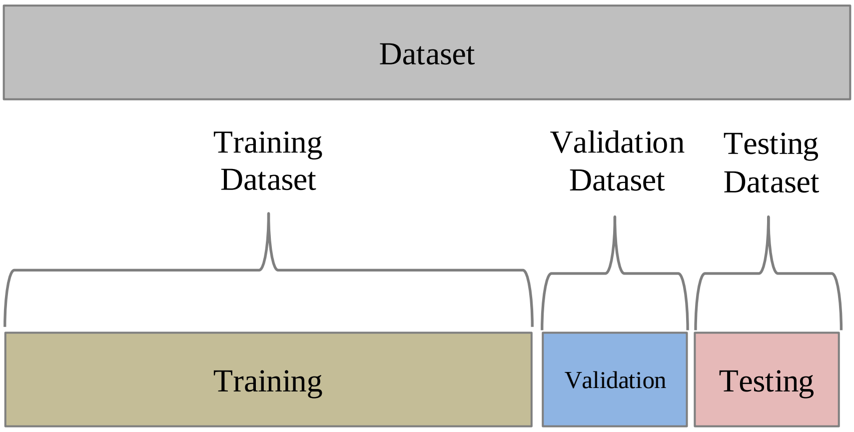

Figure 1: Visual representation of training, validation and testing phase of the PV power forecasting model

2.1.4 Basic problem formulation and algorithmic solutions

For an accurate DA and Hour Ahead (HA) PV power forecasting, configurations (model optimization based on their input parameters, combinations and hyper-parameters) of the ANN model are applied to existing PV operational data which includes NWPs and PV system data that is already monitored.

Yearly datasets of a PV system are required to develop the DA and HA forecasting algorithm. The yearly datasets are divided into three different sets to calculate the optimal parameters. The first set is the "training set", the second is the "validation set" and the third is the "test set". The yearly datasets are divided into a conventional 70:15:15% portion, where the data are taken randomly. The ANN are trained with 70% of the data and the rest 15:15% are used for validation and testing respectively. These percentages are chosen as to ensure that there is enough information for each step of the ANN creation. For the FLEXGRID purposes, it was assumed that the portioning of the data into an explicit "training set" will be used to formulate the model, the validation set will be utilized to tune the hyper-parameters of the ANN model and the testing set will be used to evaluate the performance of the model.

Furthermore, the input parameters for the "training set" and "validation set" consist of historical data. Specifically, the inputs are NWPs that includes the global horizontal irradiance (*GHI*) as well as the ambient temperature (T_{amb}). Also, in order to improve the accuracy of the ANN forecasting model, the elevation angle of the sun (α) and the azimuth of the sun (ϕ_s) calculated using solar position algorithms and utilized to the address of the angular response of the PV systems. The output that is used is the output of the reference PV systems (DC side of the PV inverter). Further, the input parameters for the "test set" are the NWPs. Testing is necessary in order to identify the model's performance.

An illustration of the implemented ANN forecasting model is shown in the Figure 2, which describes the Network Interface Diagram (NID) of an ANN model with 4 inputs, 1 hidden layer, 4 hidden neurons and 1 output.

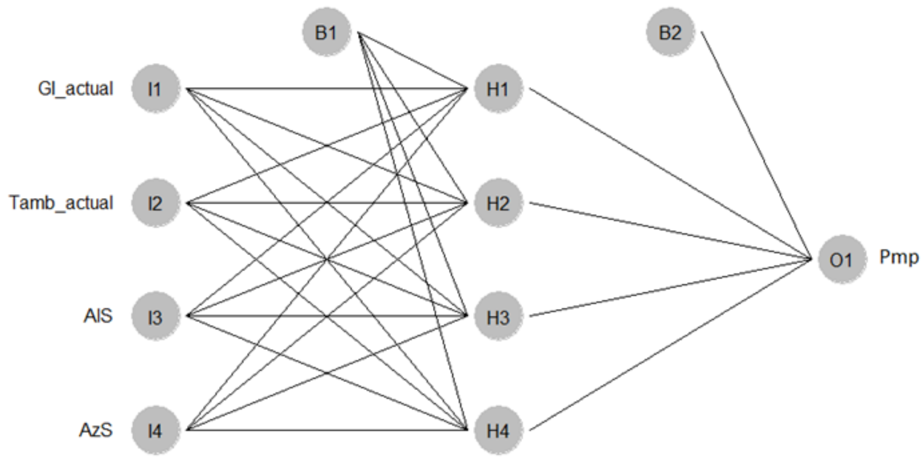

Figure 2: Network Interface Diagram (NID) of an ANN model

2.1.4.1 Hour-Ahead PV Power Forecasting

Economic and efficient operation of a power system greatly depends on the accurate HA forecast of the power demand. For the HA power forecasting, an NWP-free methodology will be followed.

The methodology for the HA is very similar to the DA PV power forecasting. The model of the HA PV power forecasting is based on a BRNN model that exploits at least yearly datasets for the training and validation set.

The main purpose of the HA PV power forecasting is to accurately forecast the power generation for the time t + 1h. In the HA model, the PV production (output parameter) at time t + 1h is obtained using the *GHI*, T_{amb} and the calculated parameters α and ϕ_s at time t. The equation that describes the HA model methodology is demonstrated in Eq.1.

$$P_{DC}(t+1) = GHI(t) + T_{amp}(t) + \alpha(t) + \varphi_s(t) \quad (1)$$

Where P_{DC} (t + 1) is the HA PV power forecasting for time t + 1, *GHI* (t), T_{amp}(t)…, are the weather measurements for time t.

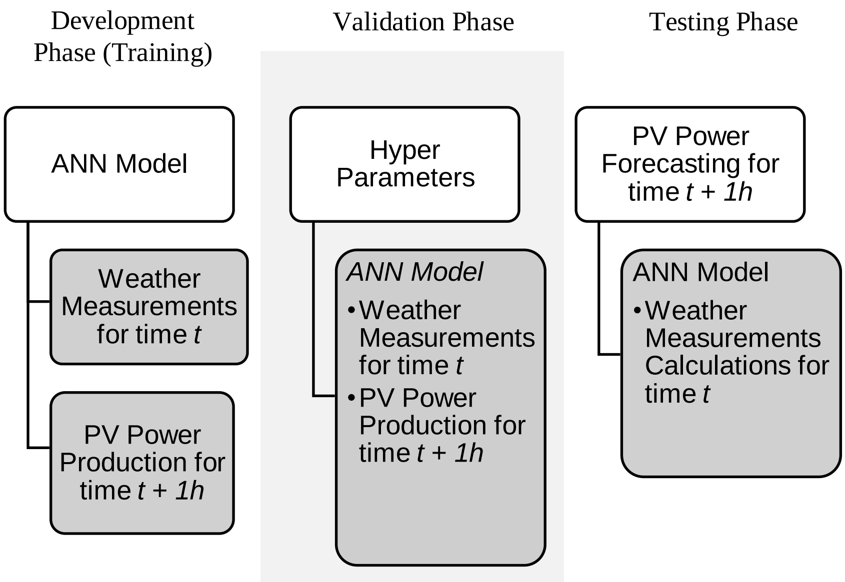

Figure 3: Training, validation and testing phase of the HA PV energy forecasting model

2.1.5 Datasets to be used for simulation setup and most important KPIs

The Key Performance Indicators (KPIs) are already defined by FLEXGRID for the RES prediction (PV power forecasting) and include: i) RES Production Curve Forecasters (RPCF), and ii) RES Production Curve Forecast Accuracy Levels (RPCFAL).

For sufficient training and testing of the ANN model that will lead to efficient and accurate PV power forecasting, at least one year of datasets are required. More specifically, historical observed PV power data (P_{dc}) and 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.

Furthermore, for the performance evaluation scenarios, a collection of PV power actual data will be compared with the forecasted data of the ANN model the day after. If data is available, the performance of the ANN model will be also tested in different PV site locations, where there are different weather conditions.

To quantify the short-term and long-term RPCFAL, statistical metrics will be used. The forecasting performance accuracy is assessed based on several predefined metrics, when the "test set" of the examined PV systems is applied to the developed forecasting algorithms. The metrics for the PV production forecasting includes the mean absolute error (MAE), which measures the difference between two actual and predicted data, the mean absolute percentage error (MAPE), which measures the prediction of the accuracy of a forecasting method, the RMSE which describes the standard deviation of the prediction errors and finally the normalized RMSE (nRMSE), in which the RMSE is normalized to the nominal capacity of the PV system.

$$MAE = \frac{1}{n} \times \sum_{i=1}^{n} \left| y_{\text{actual,i}} - y_{\text{predicted,i}} \right| \tag{2}$$

$$MAPE = \frac{100}{n} \times \sum_{i=1}^{n} \left| \frac{y_{\text{actual,i}} - y_{\text{predicted,i}}}{y_{\text{actual,i}}} \right| \tag{3}$$

$$RMSE = \sqrt{\frac{1}{n} \times \sum_{i=1}^{n} (y_{\text{actual,i}} - y_{\text{predicted,i}})^2} \tag{4}$$

$$nRMSE = \frac{100}{P_{n\text{ominal}}} \times \sqrt{\frac{1}{n} \times \sum_{i=1}^{n} (y_{\text{actual,i}} - y_{\text{predicted,i}})^2} \tag{5}$$

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

2.2 Market Price Forecasting

2.2.1 Research motivation and novel FLEXGRID contributions

Predicting electricity prices is important for all market participants since their bidding strategy and subsequently the resulting prices are based on the forecast. The innovation that FLEXGRID offers is an electricity price forecasting tool that ESPs/Aggregators can use to design the bidding strategy that will achieve the optimal trade-off between risk and profit. The proposed algorithm for forecasting electricity prices will make the best use of historically available data, resulting in high-precision forecasts. It will be a complete solution for ESPs/Aggregators through which they will make more efficient bidding (and thus scheduling and planning) decisions (cf. chapters 3-6 below).

Due to the great importance of such a tool for ESP / Aggregator, the motivation for research arises. More specifically, today's markets and future ones require participants to be able to offer the best possible quality services in their highly competitive environments. This will enable them to play a leading role and at the same time increase their profits rendering their business economically sustainable in the long term. Consequently, the forecasting algorithm must use innovative prediction techniques that will give highly accurate predictions. Research problems from chapter 3 to chapter 6 develop optimization programs/algorithms that require the availability of market predictions. This is of vital importance as optimization will be dependent on future market trends.

2.2.2 Survey on related works in the international literature

The related work can be divided into two parts. The first part concerns the trading mechanisms, which exist in each market and the interactions between the different markets. The second is about the mathematical models and techniques for predicting electricity prices in the Day-Ahead Market/Auction Based Markets.

The European electricity market is divided in several markets with different time frames. More specifically, there are markets for long-term trading, where agreements for delivery of energy are made a week, a year or even years in advance. This type of contracts usually exists in future markets. In addition to long-term trading, there are also markets for short-term trading. These are the Day-Ahead, Intraday and Balancing/Reserve market. The Day-Ahead market takes place one day before delivery is due, the Intraday market is closer to delivery time and finally the Balancing Market ensures near real-time the balance of supply and demand. The Day-Ahead and the Intraday market are usually operated by a Nominated Electricity Market Operator (NEMO), while the Balancing market is mostly operated by TSOs.

Most energy exchanges of short-term trading take place in the Day-Ahead Market. The Day-Ahead Market is an auction-based market with a single market clearing price per bidding zone. Participants can place their orders until gate closure. Each order must specify whether it is a bid or an offer. It must also determine the price and energy volume for each Delivery Period.

In terms of trading hours, trading usually starts from 00:00 CET and ends at 12:00 CET of day *d-1* and concerns the 24 hours of delivery day *d*. After gate closure, the values and energy volumes submitted are collected and the market equilibrium is calculated for each period of the following day (i.e. marginal price), as the intersection of the offer and bid aggregated curves, which gives the market clearing price and the volume of energy for the respective delivery period. Such a process is followed by multiple NEMOs, including the Nord Pool platform [25].
As for the Intraday Market, it is a continuous trading market and is an adjustment market. This market is crucial for Variable Renewable Energy (VRE) producers, who have less flexible

production technologies for which it is difficult to predict production 12-36 hours before delivery (as required in the Day-Ahead Market) [13]. This market gives the opportunity to participants to adjust their production/demand commitments according to the updated forecasts which are closer to the time of delivery. Thus, they can prevent high balancing costs which are caused by potential imbalances. It is also considered a symmetrical market, as it is a continuous trading market with a price settlement of pay-as-bid [13].

Trading hours (cf. Nord Pool platform) are usually at 14:00 CET and trading closes one hour before delivery in the Baltic and Scandinavian market areas except Estonia and Finland where it closes 30 minutes before delivery. The Figure below shows the sequence of the Nord Pool market (Day-Ahead and Intraday Market).

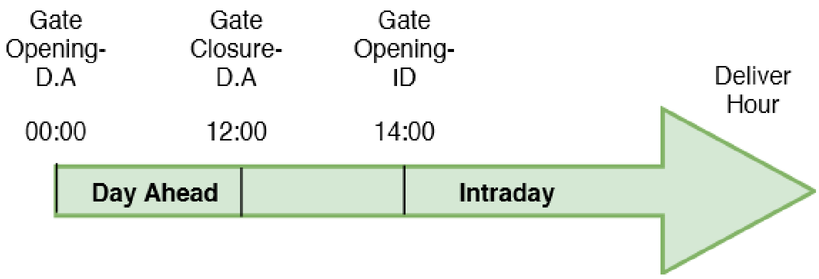

Figure 4: Nord Pool sequence for Day-Ahead and Intraday Market

Any imbalances in the Day-Ahead and Intraday markets are settled in the Balancing market, which ensures real-time balance between supply and demand. In this market, reserves are contracted beforehand, and activation of reserves occurs in case of imbalances. This market is usually operated by the TSO. For example, in Finland the Balancing Responsible Parties (BRPs) submit one day before delivery, a schedule of their production and consumption for each time slot to the TSO [14]. Then, the Balancing Service Providers (BSPs) submit bids for up-regulating or down-regulating to the TSO, who collects them at the end of the bidding period and determines the assets, which will provide balancing services. In the case of up-regulating, production increases or consumption decreases, and the price is determined by the most expensive up-regulating offer available for that time. In the case of down-regulating, production decreases or consumption increases and the price is determined by the cheapest down-regulating offer. Finally, as far as the settlement is concerned, the energy deviations of the Balancing Responsible Parties from the schedule they submitted, covers balancing costs [15]. Here the Balancing Responsible Parties are financially responsible for the imbalances caused, either positive (Supply>Demand) or negative (Supply<Demand) [16]. Figure 5 illustrates the process followed in the equilibrium market with its participants.

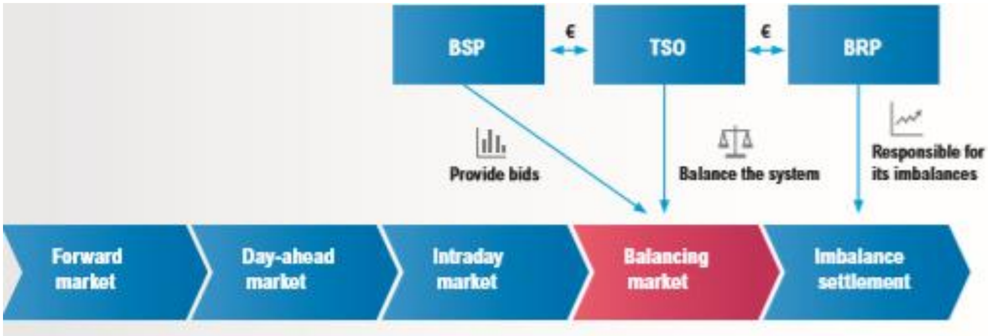

Figure 5: Balancing Market sequence. "European Network of Transmission System Operators for Electricity, 'European Electricity Balancing Guideline.'" (see pp. 4)

Two types of payments exist in the Balancing market: a) Payment for the availability of an asset (capacity) and b) Payment for utilization/activation of an asset (energy/dispatch). In the first case, the TSO pays the accepted assets to ensure the availability of the reserve at the required time slot. In the second case, the TSO pays the accepted assets for the activation of the reserve. In the case of activation of an asset, there may be compensation for both availability and dispatch. This depends on the specific operation of the market in each country [17].

Moreover, regulation services are included in the Balancing/Reserve Market. The TSO usually pre-selects the balancing bids before delivery time and due to pre-selection, the selected assets are compensated for their availability. However, there are countries in which the TSO chooses the amount for regulation it pays based on the energy price [18]. The figure below shows the timeline for reserve products.

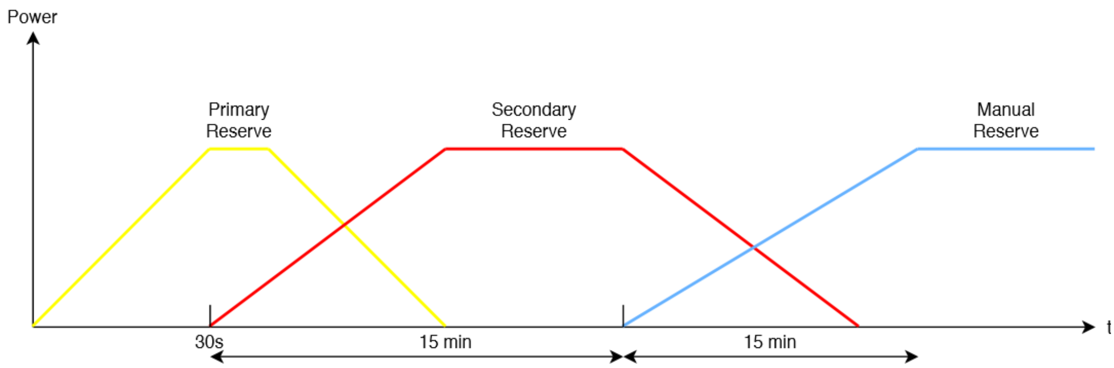

Figure 6: Timeline for Reserve Product. Pierre Pinson, presentation "Ancillary Services and regulation markets". [Online]. Available: www.pierrepinson.com .

A simple example for a better understanding of how the above electricity markets work is the following: A producer who has a PV park promises at day *d-1*, for delivery day *d*, in the timeslot between 10:00-11:00 a production of 100MWh. However, his updated forecasts show that the production will be only 80 MWh. So, there is a deficit of 20 MWh. Therefore, he can participate in the Intraday Market to cover what is left, as in this market the prices that will be offered are lower compared to those of the Balancing Market. Thus, he avoids high balancing cost that could be imposed on him for the imbalance that would be created.

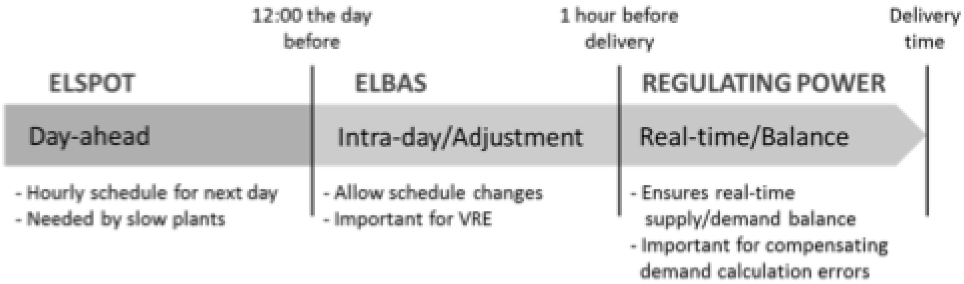

Figure 7: Market Structure at Nordic Power Market.
Market Structure at Nord Pool. Emillie Rosenlund Soysal, Ole Jess Olsen, Klaus Skytte, Jonas K. Sekamane, "Intraday Market Asymmetries-a Nordic Example", 2017.

The second part of literature is related to mathematical models and techniques for forecasting prices in the "spot market" of electricity. This usually concerns the Day Ahead Market, which is auction-based and there is a single price per bidding area. In the Day-Ahead Market as previously mentioned, participants submit their bids and offers before a specific closing time on day *d*-1 for electricity delivery every hour (or half hour) of day *d* as shown in Figure 8.

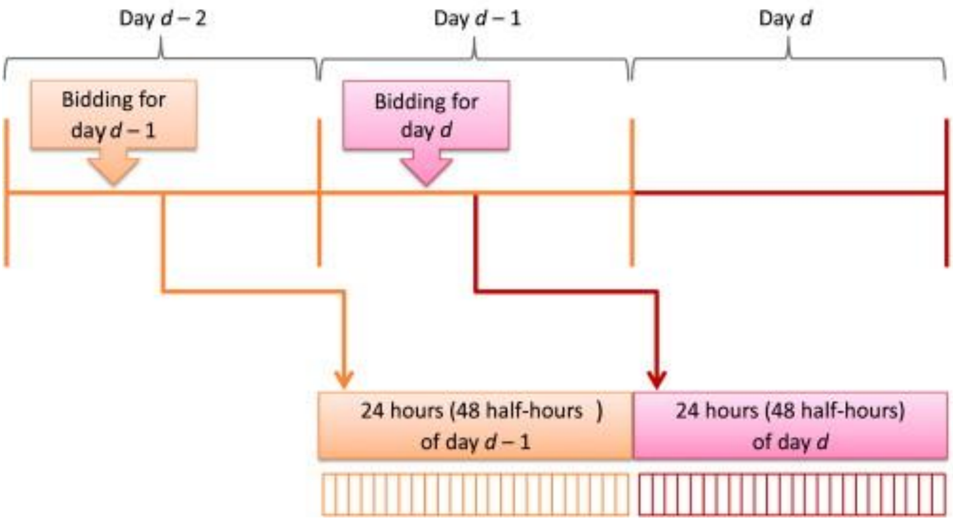

Figure 8: Gate Closure of Day Ahead Market for Day d

In recent years, various methods have been tried to predict electricity prices with varying degrees of success. Figure 9 below shows the various methods that have emerged in the international literature.

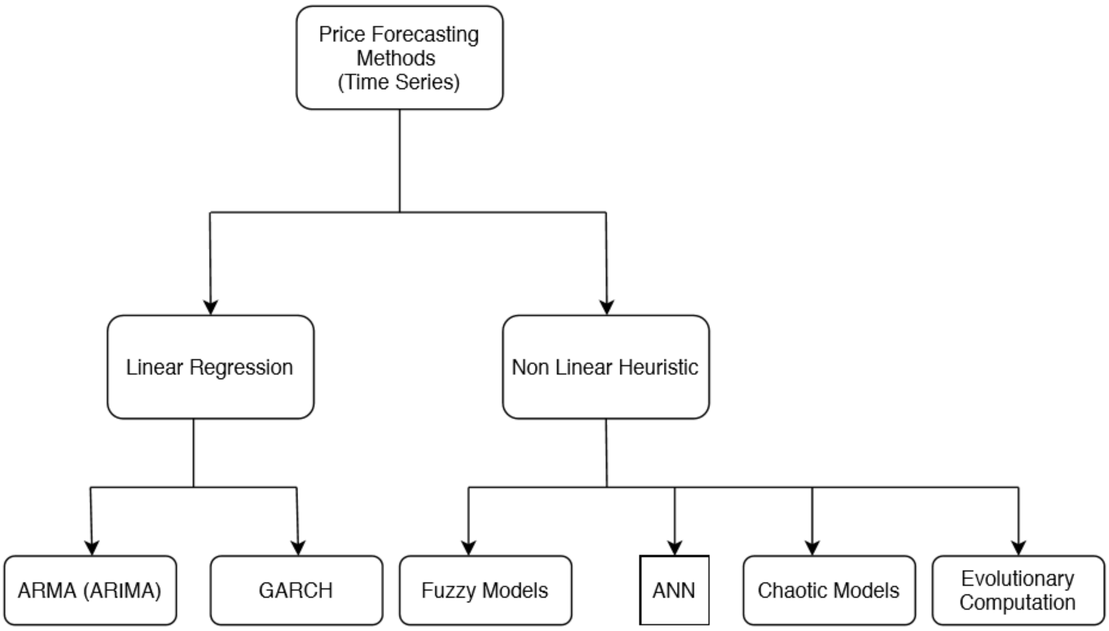

Figure 9: Diagram with forecasting methods for Day-Ahead Market

There are several methods that can be used to process a time series (electricity prices) and predict future electricity prices. Emphasis is placed on the ARMA (ARIMA) and computational intelligence methods, which, to the best of our knowledge, yield the most promising results (e.g. Artificial Neural Network-ANN). In the case of ARMA (ARIMA), various cases have shown that it gives price forecasts with quite high accuracy. The disadvantage of ARMA models is that they are suitable for stationary time series i.e. time series whose statistics remain invariant with time. The time series of electricity prices not only in general exhibit non-stationary behaviour but also their non-stationarity lacks the homogeneity that is presupposed for the ARIMA model. This led researchers to propose methodologies where ARIMA models are combined with other techniques. Towards this end, in [18], the authors combine the ARIMA model with Wavelet Transform in order to take advantage of the Wavelet Transform and further improve the accuracy of predictions.

Computationally intelligent methods combine learning elements to create approaches that can adapt to complex dynamic systems [19]. In recent years, research into electricity price forecasts in Day-Ahead Market has focused on these methods and more specifically in the combination of Artificial Neural Network (ANN) with other methods. In [20] and [21], the authors combine ANN with Wavelet Transform and the results are very good in terms of accuracy.

A method that is becoming popular is the one proposed by Huang in [22]. This method is computationally cheaper and faster than other ANN based methods. This method is called Extreme Learning Machine, and it uses a different notion of learning than the optimization based one that ANNs use. The inputs weights and biases are selected randomly and the features that are used for decision (forecasting) are determined by solving a simple linear equation. This method, Extreme Learning Machine can be cast as a Single Hidden Layer

Feedforward Neural Network (SLFN) and is the basis for many articles written and related to electricity price forecasting in the Day-Ahead Market.

The simplicity and speed of ELM renders it amenable to statistical techniques that yield prediction and confidence intervals as it has been demonstrated in [23], where the authors combined Extreme Learning Machine with Bootstrap Sampling. The ELM algorithm was selected as the basic algorithm to be developed further for forecasting as it is subsequently described.

2.2.3 Basic system model to be followed

The basic algorithm that will be used to develop the electricity price forecasting methodology is the Extreme Learning Machine (ELM). This will be combined with Multi-Resolution Analysis (MRA). To address the uncertainty of predictions, prediction intervals will be created using Bootstrap Sampling.

It is claimed in [22] that the ELM is a state-of-the-art Single Layer Feed-forward Network (SLFN) algorithm, because it solves problems with shorter modelling times at a comparable or better performance to traditional algorithms. The input weights and biases are randomized so that the output weights have a unique least-squares solution solved by the Moore – Penrose generalized inverse function.

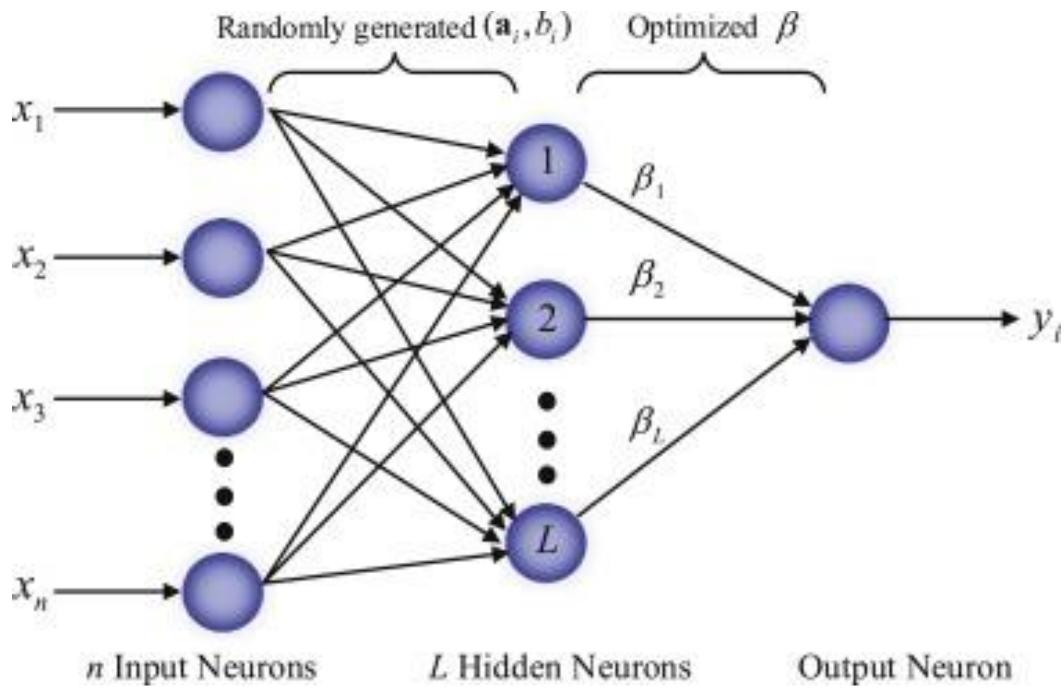

Figure 10: A typical structure of ELM

Suppose an ELM with L hidden neurons and activation function g(x) is used to model N arbitrary data samples(x_i, t_i) , $x_i \in R^n$ where x_i is a sample vector and t_i its target value. Mathematically, the ELM is described by:

$$\sum_{i=1}^{L} g_i(x_i)\beta_i = \sum_{i=1}^{L} g\left(w_i x_j + b_i\right) = t_i \tag{6}$$

where w_i is the weight vector connecting the *i*-th hidden neurons and the input, β_i is the weight vector (or output weights) connecting the *i*-th hidden neuron and output and b_i is the bias of the *i*-th hidden neuron.

The basic steps of ELM are the following:

Step 1: Identify Training sets X=$\{x_i, y_i\}$ and Testing set.

Step 2: Identify Activation Function $g\{x\}$ and Hidden Node Number *L*.

Step 3: Random selection of input weights and biases.

Step 4: Calculation of the hidden layer output *H*.

Step 5: Calculation of the output weight β.

In the context of forecasting, x_i are vectors containing historical prices and y_i the vectors of the prices that must be predicted. Note that for the testing sets these values are known and are those used to train the ELM. In the testing set these values are also available but they are only used to test the performance of the trained ELM.

Even though there are many choices of activation function the one that is widely used is the sigmoid one. It is a non-linear function that takes values between (0-1) and is given by

$$g(x) = \frac{1}{1 + e^{-x}} \tag{7}$$

Equation (6) can be compactly written as,

$$H\beta = T \tag{8}$$

where *H*

$$H = \begin{pmatrix} g(w_1, b_1, x_1) & \cdots & g(w_L, b_L, x_1) \\ \vdots & \ddots & \vdots \\ g(w_1, b_1, x_n) & \cdots & g(w_L, b_L, x_n) \end{pmatrix}_{n \times L} \tag{9}$$

is the Hidden layer matrix.

The output weights can be calculated through the pseudo-inverse.

$$\beta = H'T \tag{10}$$

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

2.2.3.1 Separation of Data into Training and Testing sets

The available data is separated into training and testing sets. According to the literature, usually 80% of the available data is defined as a training set and the remaining 20% is defined as a testing set. In addition, according to the closing of the gate which is usually at 12:00 CET, the participant must have the predictions around 11:00 CET. Regarding the separation of data into training and testing sets, this is done according to the available data. If, for example, data are available for four consecutive days (4x24 = 96 values), the training set will be the data of the first three days and the goal is to predict the 24 values of the fourth day. The actual data of the fourth day will be used to calculate the accuracy of the algorithm (e.g. RMSE calculation). This example is shown in Figure 11.

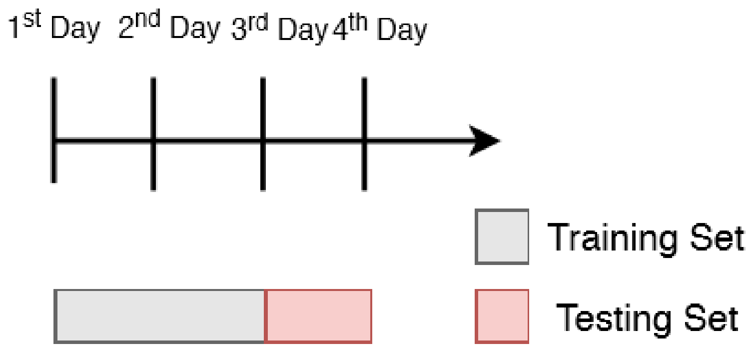

Figure 11: Data separation in training and testing set

2.2.3.2 Multi-Resolution Analysis

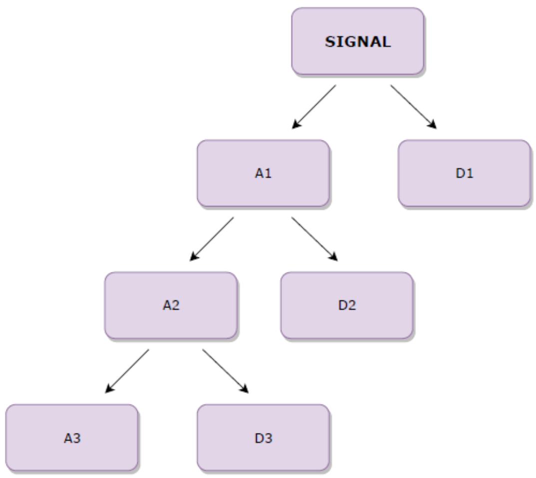

Figure 12: Wavelet Transform Decomposition (3 levels)

As it was discussed in the literature, the electricity price time series exhibit non-stationarity. A basic characteristic of such time series is that they contain multiscale features. MRA is a mathematical tool that implements multi-scale signal analysis. The basic steps of MRA are the so-called decomposition and reconstruction. In a decomposition step, details (high frequency content) of the signal are removed to yield a lower scale approximation, denoted by A. The details removed are stored to a higher frequency signal called the detail and denoted by D. Mathematically, the detailed signal can be computed as a projection of the original on a basis consisted of wavelet functions and respectively the approximation is a projection on a basis consisting of the so called scaling functions. There are various different bases that could be selected for analysis and usually the selection is based on the features that one would like to emphasize [24]. The overall decomposition is depicted in Figure 12, where as it can be seen, the subsequent basic decompositions are implemented on the resulting approximations only. Each separate row of decomposition in Figure 12 is called a level.

The different approximations and details at each level have simpler statistical properties that can possibly be exploited by ELM for better forecasting accuracy. Two widely used wavelet and scaling functions are the Haar and Daubecies ones.

Since the various decompositions are projections on basis functions they can be simply seen as the following additions of the various components:

Level 1: $S = A_1 + D_1$ (11)
Level 2: $A_1 = A_2 + D_2$ (12)
Level 3: $A_2 = A_3 + D_3$ (13)

and combining equations (11), (12), (13) where the original signal is obtained as follows:

$$S = A_3 + D_1 + D_2 + D_3 \tag{14}$$

2.2.3.3 Construction of Prediction Intervals by Bootstrapping

Bootstrap method is a sampling method with replacement [20]. That is, from an original set Bootstrap through replacement creates new samples. Subsequently, Bootstrap samples can be used to estimate an estimator’s distribution. A representation of the Bootstrap method is shown in Figure 13.

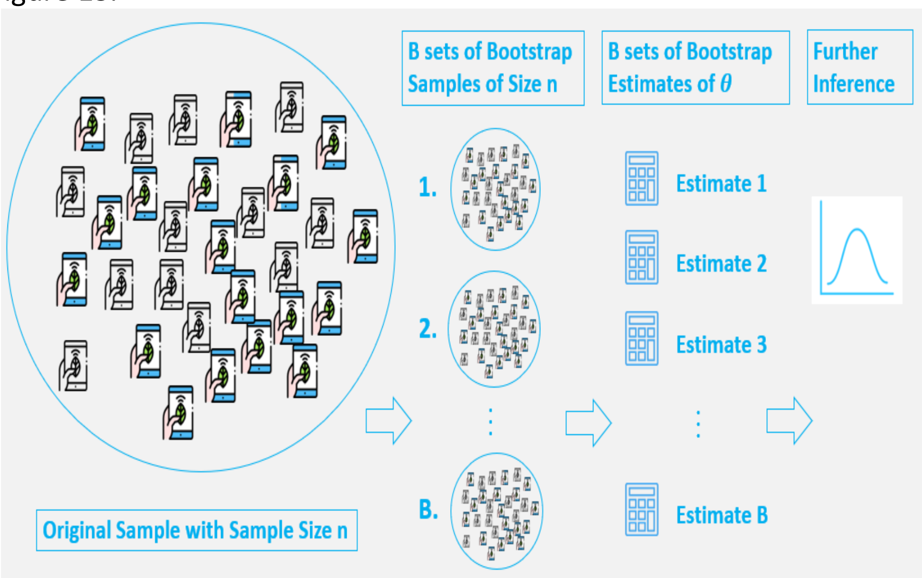

Figure 13: Bootstrap method

For example, let us assume that the original data sample is the training sample $\{x_i, y_i\}_{i=1}^{n}$. The error (or residual) (e) between actual data and forecasted data by the algorithm can be calculated with the use of equation (8). Therefore, rewriting equation (8) results in the following equation:

$$e = T - H\beta \tag{15}$$

Then, New Bootstrap data sample (y_i^*) is created as follows: The bootstrap errors (e^*) are drawn randomly (with probability $\frac{1}{n}$) with replacement from sample that is constructed from the actual errors given by (eq.15). The new data sample is created from the randomly drawn errors using the following equation,

$$y_i^* = predicted\ prices + e^* \tag{16}$$

This process (calculation error (or residual) (e) and new bootstrap data sample (y_i^*)) is done several times to get a number of bootstrap replicates and then calculate the Prediction Intervals. Figure 14 shows a diagram of the Prediction Interval.

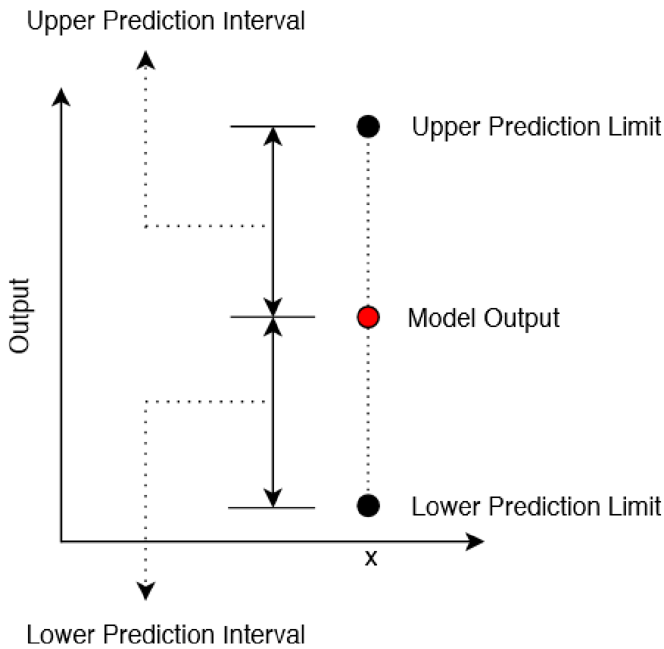

Figure 14: Prediction Interval diagram (example)

Note that the theoretical basis of the above is the fact that e is Independent and Identically Distributed (i.i.d) [23].

2.2.3.4 Indicative results from State of the Art methodologies

The results for the State of the Art resulting methodology are summarized in Table 2.

Table 2: Indicative results from State of the Art methodologies

Season	Model	MAE	MAPE (%)	RMSE	Weekly-MAE (%)
Winter	ELM	2.028	4.347	1.354	
	W-ELM		6.108		
	W-ELM+Ensebles		6.010		
	W-Kernel-ELM	2.620	4.50	4.17	4.78
	FLEXGRID Model	**TBD**	**TBD**	**TBD**	**TBD**
Spring	ELM	2.302	10.264	3.178	
	W-ELM		5.128		
	W-ELM+Ensebles		4.937		
	W-Kernel-ELM	0.84	1.65	1.14	1.65
	FLEXGRID Model	**TBD**	**TBD**	**TBD**	**TBD**
Summer	ELM	10.167	21.880	16.588	
	W-ELM		5.872		
	W-ELM+Ensebles		5.843		
	W-Kernel-ELM	1.02	2.02	1.44	2.05
	FLEXGRID Model	**TBD**	**TBD**	**TBD**	**TBD**
Autumn	ELM	7.319	12.736	10.382	
	W-ELM		6.428		
	W-ELM+Ensebles		6.056		
	W-Kernel-ELM	3.30	5.17	5.82	5.78
	FLEXGRID Model	**TBD**	**TBD**	**TBD**	**TBD**

2.2.4 Basic problem formulation and algorithmic solution

The problem that we want to solve concerns the prices of the Day-Ahead Market. That is, the methodology and consequently the algorithm can be used for price forecast that are based on auction and are uniform-priced. Any market that meets these conditions, will be able to use the proposed methodology. In addition, the algorithm can then be used for the Balancing (reserve) Market, which shares these characteristics.

As mentioned in the literature survey section, the trading hours for the next 24 hours are from 00:00 CET until 12:00 CET (gate closure). Therefore, the algorithm will follow the following framework:

Market price forecasts for day d are required on day d-1before 12:00 CET. Results for day d-1 are also available on day d-2 at 12:43 CET. Thus, the actual market price forecast for day d can be made between 12:43 CET on day d-2 and 12:00 CET on day d-1. Figure 15 shows the time framework for the Day Ahead forecast.

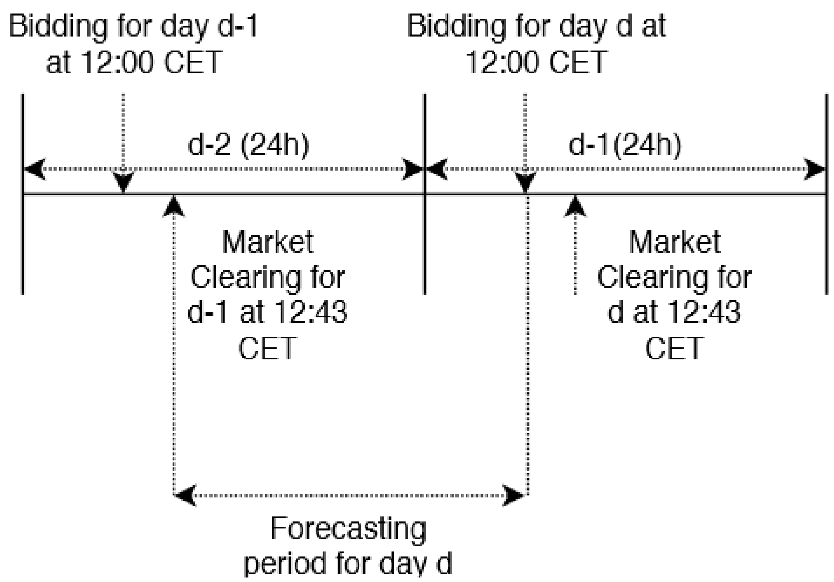

Figure 15: Framework of the Day Ahead price forecast

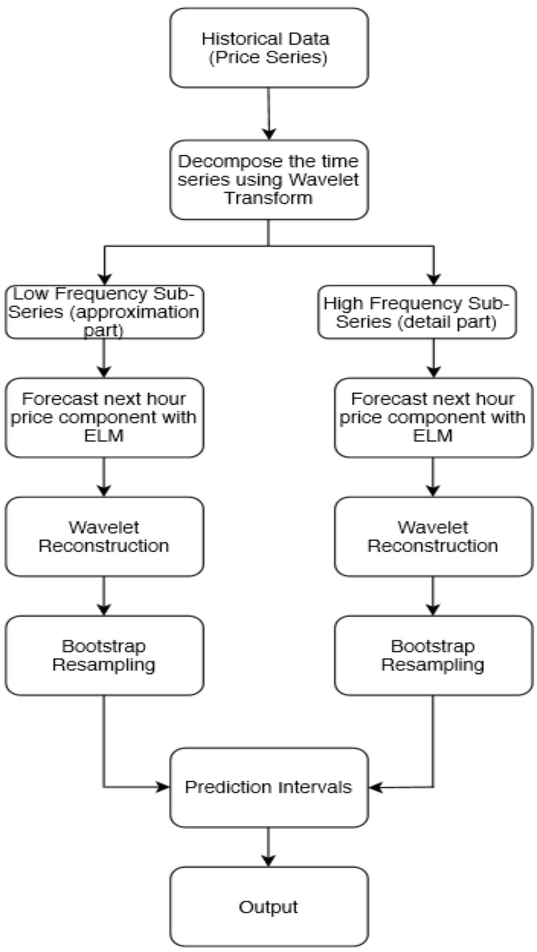

Figure 16: Flowchart of proposed algorithm

The proposed algorithmic solution has the following basic steps:

- Step 1: Wavelet Multi Resolution Analysis is applied to the available data (price series) and the coefficients (approximation and details) are obtained.
- Step 2: ELM is applied to each decomposition level.
- Step 3: Apply wavelet reconstruction to predict the time domain prices.
- Step 4: Apply Bootstrap Resampling and create prediction intervals.

Regarding the flowchart of the proposed algorithm (Figure 16), given the fact that FLEXGRID research is still in an early stage, it can still change depending on the results that will be obtained. Any changes that occur will be reported in detail in the next WP3 deliverables (i.e. D3.2 and D3.3).

2.2.5 Datasets to be used for simulation setup and most important KPIs

In the context of FLEXGRID project, the advanced price forecasting algorithms that will be developed should be able to utilize data from various markets (wholesale, day ahead, real time) and give results with fairly high accuracy. As already mentioned, the Day Ahead Market is based on an auction-based process and prices are uniform. The input data of the algorithm will be historical data (hourly values), which are available on the Nord Pool website [25]. In addition, there are thoughts of using Australian Day Ahead Market prices, which are available on the A.E.M.O (Australian Energy Market Operator) website [26]. Thus, a comparison of the results and important conclusions can be made.

The main competition of the proposed method is a class of algorithms using Support Vector Machine (SVM). This method can analyse data used for classification and regression. In other words, the SVM model can represent data as points in space so that the data is divided by a space. New data is then mapped to the same space and is considered to fall into a category based on the side of the gap into which they fall [27].

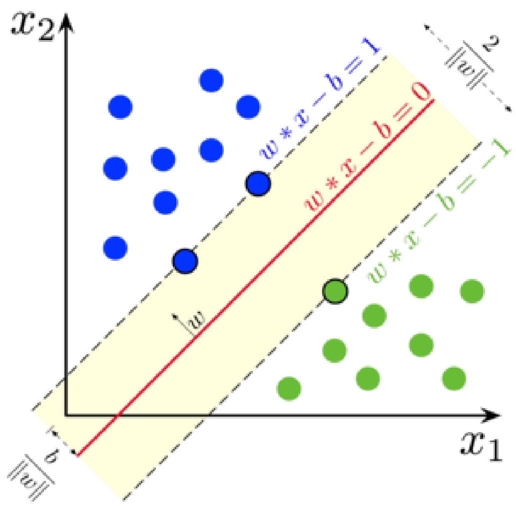

Figure 17: Support Vector Machine (SVM) example

Also, SVM does not have random configuration like ELM so the result remains the same every time the algorithm runs. In addition, SVM has active learning which is considered an optimization method which reduces the model build time. That is why ELM has a longer training time but a lower testing time. As for the accuracy of the two methods, they are the same and therefore considered ideal for prediction [28].

Another method that ELM can compete with is Least-squares support-vector machines (LS-SVM). This method is a different approach to SVM. In this method a set of learning algorithms analyse the data and find patterns that are used for sorting or regression. Also, the solution results from solving a set of linear equations instead of convex quadratic programming [29]. Thus, all this contributes to the conclusion that this method can give better detection results compared to ELM. However, ELM gives better function approximation capability and has a shorter training and testing time [30].

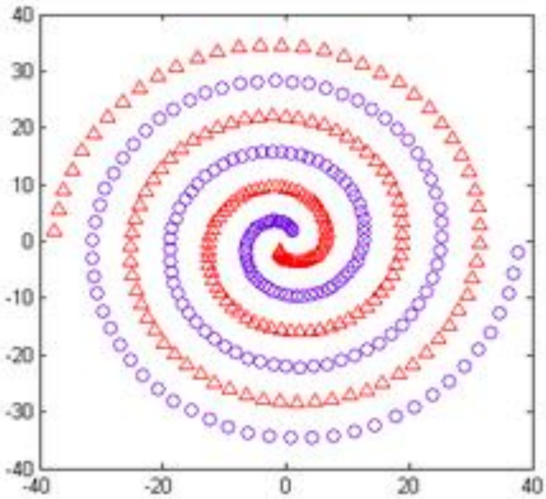

Figure 18: Least-squares support-vector machines (LS-SVM) example

The accuracy of the results that this algorithm will give can be calculated from the standard formulas that exist. Also, the results obtained from the standard formulas are described in Table 2. Equation (17) gives the Mean Absolute Percentage Error-MAPE, which is the difference between the actual values (Y_i) and the forecasted values (y_i). In addition, Mean Squared Error-MSE (eq.18) gives the mean square difference between the actual value (Y_i) with and the forecasted value (y_i).

$$MAPE = \left(\frac{1}{n}\sum_{i=1}^{n}\frac{|Y_i - y_i|}{Y_i}\right) \times 100 \tag{17}$$

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(Y_i - y_i)^2 \tag{18}$$

For more detailed list of KPIs, see chapters 3-7. In these chapters, research problems are explained that use market price predictions to enhance the ESP’s related KPIs.

3 ESP minimizes its OPEX by optimally scheduling the consumption of end users, production of RES and storage assets

3.1 Research motivation and novel FLEXGRID contributions

The focus of the HLUC_02_UCS_01 is on developing the most appropriate business strategy for the Energy Service Provider's (ESP) operational expense (OPEX) optimization efforts. To do so, this use case scenario will investigate how behaviour of the end users, production of renewable energy sources (RESs) and storage assets affect the ESP's OPEX. The research problem should result with a model that minimizes ESP's OPEX by optimally scheduling the consumption of end users, production of RES and storage assets given the input parameters and constraints.

Considering the role of the ESPs, the range of the responsibilities and areas where they are able to operate in, strategies that are sub-optimal may significantly reduce profits and even potentially endanger sustainability of the company's business model. First and foremost, one needs to have the definition of the ESP in mind to understand its motivation and direction of this research in general. In the most general case, ESP is a profit-oriented company, which may make contractual arrangements with various types of flexibility assets (e.g. DSM, RES, storage) [31]. The figure below illustrates the ESP's role and even more it tries to point to the fact that an ESP takes part in various markets, such as: i) wholesale, ii) retail, iii) reserve and iv) (potential) flexibility market proposed by FLEXGRID.

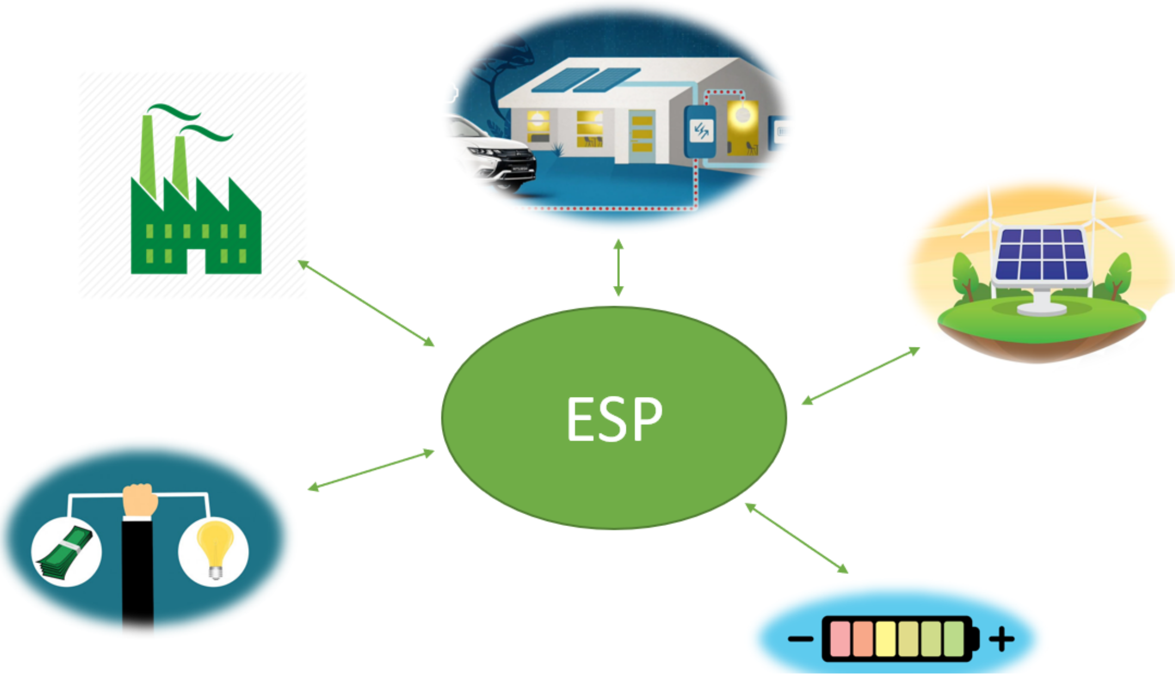

Figure 19: ESP's area of interest

This wide area of mutually connected areas, where ESP is qualified to participate in, presents a very interesting research topic, mainly because the degrees of freedom that ESP has in scheduling the various types of its FlexAssets. Both academic and commercial communities are very interested in exploring how to exploit various markets to provide safe, reliable and profitable power delivery services, especially nowadays when long term paradigm is shifting towards penetration of the distributed energy sources (with emphasize on RES). Furthermore, profit may be the main motivator to quickly integrate intermittent energy sources. Should high RES penetration present non sustainable business model for some ESPs, they will simply run out of business when high RES penetration becomes reality or provide high resistance to the introduction of greener, but less controllable, electricity generation technologies. So, the motivation to perform research on this topic comes from multiple directions. From simple profit-oriented motivation to the ecology aware forward-thinking mentality. One is certain, without sustainable business models, not only high RES penetration will in general not happen as quickly as planned, but the system could be more prone to failures as ESPs (and other key-players) won't be motivated to take measures needed to facilitate such high stake of intermittent and non-controllable energy sources in the energy mix.

On the other hand, novel FLEXGRID contributions may be classified into multiple categories:

- Holistic high-quality scenarios considering multiple and diverse FlexAssets
- Scheduling based upon highly precise input data
- In-house developed forecast models for:
    - RES production (weather forecasts)
    - End-user consumption forecasts
    - Market prices' predictions
- Laboratory battery testing
- Precise energy storage (battery) models

High quality scenarios will try to encompass all realistic cases that may happen in the near future (i.e. from current situation, where RES penetration is still an ongoing process to the expected high RES stakes in the overall energy mix of the observed network). This research argues that depending on the amount of energy storage systems (ESSs) and RES, for an ESP to perform in an optimal manner, schedule of its assets (owned or solely managed) varies a lot due to specific constraints that each respective generating (or storage) unit brings to the system. Depending on the available data, the final model will be as generic as possible to satisfy the needs of each ESP to the greatest extent possible and to have really clear overview how different scenarios (network setup, energy mix…) affect the overall performance of an ESP in the electricity market. Scheduling based upon highly precise input data in a way extends previous stated contribution. The quality of the scheduling algorithm relies heavily on the quality of the input data, so great efforts are put in obtaining realistic (preferably historical or even real-time) data. In cooperation with industry partners involved in the project and our own research efforts, we believe to satisfy the needs for the high-quality input data. Contributions to this research topic, but also for others, present forecast models. Improvement in the forecasting precision (in all categories) has improvement in FlexAssets' scheduling. One very important and sometimes neglected aspect, where FLEXGRID project also wants to deliver contribution is battery modelling. Laboratory battery testing is performed with various types of batteries and more precise energy models are to be delivered. All above mentioned precision improvements lead to better models, which will lead to better performance evaluation results. Although those results may present lower profit margins than algorithms developed in the past years, they will be more precise, thus reducing balancing costs. In the end, ESPs will indeed generate more profit, as the model will simulate real-life operations (with regards to constraints) in a very precise manner, leaving not much room for possible mistakes and corrective actions that result to undesired balancing costs. All in all, a holistic and comprehensive approach should result in outperforming current solutions.

3.2 Survey on related works in the international literature

The scope of this research is very broad. It deals not only with pure scheduling of the FlexAssets under its management, but it also considers optimal bidding strategies and precise modelling of the FlexAssets (mainly batteries) accompanied with the precise forecasting algorithms (market prices, end-user consumption and RES production). To conduct an extensive and detailed survey on the related works in the international literature, it was necessary to investigate both the related works that cover the whole topic (or its majority) and to divide the research to its most important components (mentioned above).

This research considers scheduling of all units in the system that are in a way controllable, but to obtain good insight of what is current state of the art progress, research papers concerning scheduling of the specific units (e.g. batteries, load shifting, etc.) were also examined. Energy storage systems (especially batteries) are becoming integral part of modern networks. So, a great amount of research papers about optimal use of batteries are available. One group of articles deals how battery storage units act almost independently on the electricity markets [32]–[37], while others investigate the cooperation with other units [8]–[15] (i.e. forecasting modules). In many cases, the distinction between those two categories cannot be clearly determined, so perhaps the most important fact is what the expected end-result is. Great amount of papers investigate how to enhance system's reliability and safety with increased penetration of intermittent renewable generation [41], [42], [44], [46] decrease the pollutants emission [32], and, on the other hand, how to maximize profit (or reduce costs) [32], [37], [38], [42], [45]. These are highly interesting topics in the academic and industrial community. Many of the observed articles use predictions to enhance their models. Authors in [45] state that they used load and generation power predictions, but the model lacked weather forecasts which could further improve the results. [43] 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. Authors in [47] developed 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 [36] that consider battery characteristics in more detail.

Besides ESS' management, demand-side management (DSM) was also considered. By definition, DSM is an action taken on the consumers' side to optimize energy consumption [48]. Whether the DSM is manual, semi-automated or fully automated, it has the ability to switch off eligible loads when overall system demand needs to be reduced and vice-versa. In other words, the resulting major areas of interest for DSM are load shifting and load reduction [49]. Depending on the available controllable assets, end users' preferences and the configuration of the network, different units may be controlled in different manners in each DSM concept. For instance, in [48] the main emphasis is on shifting the power consumption of the sprinkler pump, batteries, residential consumers (for the critical time periods were detected critical devices that could help in preserving the energy balance – e.g. washing machine around noon) and the heat pump. Authors in [49] consider DSM for residential use. They emphasize on smart-meters and users' willingness to participate in the program as key prerequisites for any DSM program. Although they have developed DSM for residential users in a smart microgrid, they don't mention RES integration. [50] is much closer to the problem observed in this chapter. They have modeled 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 uncertainty 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 pollutants' 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 [51]. ESP's objective is cost minimization, and end users' objective is to get as much economic compensation as possible for giving 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 [52], 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 [53]. Bruninx et al. in [54] present a very interesting model applicable to the research conducted under the FLEXGRID project. They have combined i) a Stackelberg game between a price-making demand response aggregator and a market operator, ii) chance constraints accounting for the limited controllability of demand response loads, and iii) a Nash Bargaining Game to represent the interaction between the DR providers. Analysis of the case study has shown how aggregator may lower wholesale prices and how it may manage limitedly controllable resources.

Optimal bidding strategies present also important research point regarding this chapter's research problem. Kardakos et al. [55] describe the optimal bidding strategy problem of a commercial virtual power plant, which participates in the day-ahead electricity market. The term "virtual power plant (VPP)" is defined as "a network of decentralized, medium-scaled power generating units such as wind farms, solar parks, and Combined Heat and Power (CHP) unit, as well as flexible power consumers and storage systems" [56]. As the concept of a VPP fits perfectly with the FLEXGRID paradigm, the mentioned article's relevance is certainly non-negligible. In similar manner, Contreras-Ocana et al. consider the interaction between an aggregator, strategically participating in the wholesale market, and distributed, perfectly controllable energy storage systems.

3.3 Basic system model to be followed

ESP's OPEX optimization problem is mostly dependent on the scenario quality, battery modelling and demand response (demand-side management) schemes.

To truly develop high quality scenarios, various cases will be examined and then potentially developed and tested. ESP will be primarily considered as an aggregator under whose jurisdiction are batteries and renewable energy sources, but even more than a pure aggregator, ESP is also a DR contractor. Worth mentioning is the fact that the basic difference between an ESP and aggregator is that the ESP acquires the generation, RES and battery assets, while the aggregator controls the assets that end energy prosumer possess. In the most common scenario, there is no need that ESP is network aware and in general it does not operate the network. Somewhat more specific case is one concerning Badenova/bnNETZE, as it is both ESP and a DSO, thus its case would certainly be network aware (cf. chapters 5 and 6 below).

ESP, the central market actor in this use case scenario, observes conventional markets, but also potential distribution level flexibility market (DLFM) to place its bids in an optimal manner concerning the OPEX minimization efforts. It is important to mention that each market is thoroughly examined, and ESP respects all given constraints and conditions that specific market contains. A little bit more specific is the DLFM proposed by FLEXGRID, where

Figure 20: Different battery types

there is still no exact formulation and thus there is much room for FLEXGRID to investigate what different configurations may cause.

Furthermore, as battery modelling may considerably influence final results, extensive laboratory testing of different battery types is being conducted. **Error! Reference source not found.** shows different battery types used in laboratory (i.e. TRL 5) to determine realistic charging and discharging characteristics for each type. By charging and discharging respective batteries with different C rates (“A C-rate is a measure of the rate at which a battery is discharged relative to its maximum capacity” [57]), the idea is also to enhance expected lifetime prognosis. This all should result in more precise mathematical modelling of energy storage behaviour and, consequently, more precise model as a whole, which should save ESP the trouble of balancing costs.

In order to optimally schedule its FlexAssets, ESP will not only rely on precise battery modelling, but FlexForecasts presented in the previous chapter should also present a powerful tool. It will provide the ESP insight about:

- Market prices predictions
  - Day-ahead
  - Intraday
  - Reserves
- Production curves (RES)
- Load curves

All above mentioned will be encompassed in a model through the three following sub-modules developed as part of FLEXGRID’s FlexSuppliers’ Toolkit (FST), namely:

- Forecasting engine
- Optimal bidding algorithm
- Optimal scheduling algorithm

The whole model is constructed in such a manner to be applicable in various cases, depending on the laws and market regulations, which may vary from country to country. Different cases will then be evaluated and proposals with comments on pros and cons of each case will follow. Throughout the whole research process, it is not neglected that electrical power market is still emerging, thus great effort is being put to model, test and evaluate different cases so the relevant authorities have the best input possible when deciding on future binding regulations.

3.4 Basic problem formulation and algorithmic solutions

The mathematical model is formulated as a single level problem. Objective function considers energy trading actions (operational expenses) and penalizes them according to their respective cost with the goal of minimizing them, taking into consideration also the profit as important factor. According to the needs and available data, the objective function may be modelled in various ways. It could be solely deterministic (the most primitive solution), while it could also be stochastic and give the user an overview on how the expected profit should look like, or it could be robust and present the user profit in the worst-case scenario.

Prerequisite for solving the problem is a very realistic, mathematically formulated, model. In that manner, the following constraints consider all the most relevant characteristics of the involved entities.

Starting with the energy storage systems, much has already been written about how FLEXGRID research efforts include battery modelling enhancements. Following deliverables (i.e. D4.2 and D4.3) will present more about progress done and here are only generally listed the most important constraints regarding energy storage systems:

- Charging/discharging power limit
- Charging/discharging efficiency factors
- Charging/discharging curves
- Battery capacity (state-of-energy (SOE) cannot exceed given limit)

To precisely model load shifting and demand response services in general, it is important to include inflexible and flexible load demand curves, alongside with the RES production curves. Shiftable loads have the liberty of executing a specific task in a wider horizon, but the task still needs to be executed in a given timeframe. Furthermore, DR users may give the permission to the DR contractor to curtail some of the demanded power (not below some agreed boundary, under which would cause too much of inconvenience of the end-user). Constraints also include different market restrictions on which ESP places its bids and offers in such a way to minimize its operational expenses. List of the most general constraints include energy balance (Demand=Production + Market Purchased Qt.) and in the case of Badenova/bnNETZE, network constraints.

According to the described problem and above-mentioned constraints, the following list presents the main variables of this use case scenario research problem:

- SOE of ESS
- Charging/Discharging power of ESS
- Bids/Offers on different electricity markets

The most important parameters are:

- ESS characteristics
- RES max. output
- Market prices
- RES production curves
- Consumption curves

3.5 Datasets to be used for simulation setup and most important KPIs

The following table summarizes the data to be used for simulation setup:

Table 3: Datasets to be used (tentative list)

Hourly day-ahead energy market prices	Hourly active power production**
Hourly balancing market prices	Hourly active power consumption**
Price bids and capacity offers in the Reserve Market	ESS data – energy/power rating, charging/discharging efficiencies
System's Upward/Downward reserve requirements by the TSO	(Distribution Network data) *
Data (capacity and cost) of Flexibility Suppliers (DR aggregators, batteries, etc.)	

*In Badenova/bnNETZE case
**For the observed region/zone

Most important KPIs are:

- Balancing costs
- RES curtailment
- Congestion occurrence frequency
- Objective function (profit/cost reduction)

Regarding the most important KPIs, the objective function itself is not the most relevant KPI. But the objective function may vary in different versions of the model/algorithm and consequently the most relevant KPIs may be differently prioritised (reliability vs. profit etc.) Should the objective function be robust, it will (by its architecture) produce the least favourable results as a safety measure for the ESP to know what happens in the worst-case scenario. On the other hand, stochastic or even chance-constrained models are more risk-prone, and as such will produce somewhat more favourable results which are then to be validated via simulation and laboratory testing (especially consequent balancing costs). In short, having chosen the type of the objective function, still the output results need to be somehow validated. Normally, regarding the type of the objective function, emphasize could be on different KPIs.

Balancing costs could present one of the most important KPIs for this research problem, regardless of the objective function type. They are a really good indicator how precise the model is. Should inaccuracies in any of aspects of the model (battery modelling, forecasts, …) be significant, this will consequently raise the balancing costs. Analysis between the balancing costs and different scenarios utilized could present a good argument in discussion which algorithm to use for which purpose.

Furthermore, RES curtailment and RES incorporation in the system in general are also KPIs to consider, especially regarding the current green paradigm. Similar to the balancing costs, analysis of the RES curtailment between different scenarios used may significantly boost ESPs certainty what scenario to user for what purpose.

Regarding the DSO, it is interesting to notice how the developed models (deterministic/stochastic/robust) contribute to the system stability and reliability or even cause potential problems in the distribution network's operation.

4 ESP minimizes CAPEX by making optimal investments on RES and FlexAssets

4.1 Research motivation and novel FLEXGRID contributions

Electricity sector has been relying in a big monopolistic market structure in the past. There was usually one big vertically integrated company that included generation, transmission, distribution and retail services. Nowadays, the situation is completely different. EU is promoting and implementing deregulated and liberalized electricity markets with a growing share of renewable energy sources (RES). “Clean energy for all Europeans” is the legislative framework that all EU member states are to follow in order to (as fast as possible) adopt modern electricity market structures, which are oriented towards high RES penetration, high energy efficiency and open market paradigm [58].

One of the definitions of the free market is the following: “An open market is an economic system with no barriers to free-market activity. Anyone can participate in an open market, which is characterized by the absence of tariffs, taxes, licensing requirements, subsidies, unionization, and any other regulations or practices that interfere with naturally functioning operations. Open markets may have competitive barriers to entry, but never any regulatory barriers to entry [59]”. Observing the quoted definition, for the purpose of this research it is important to emphasize on the term “competitive barriers”. Transmission and distribution system operators present natural monopolies and they have stayed regulated service and non-discriminatory towards any interested party. But, other roles are open to interested parties, which satisfy certain requirements (e.g. generator with specified technical requirements) that are present to ensure stable and reliable power distribution operation. Assuming that greater competition raises market efficiency, and greater competition comes with lower entry barriers, one of the key aspects is to lower entry barriers such as capital expenditures (CAPEX) (e.g. optimal strategy may lower required capacity of the battery storage units, and, thus, lower the initial investment). Lower CAPEX will allow smaller players to actively participate in the power market and this is a crucial part of the EU plan towards clean, decentralized, prosumer oriented distributed power supply paradigm.

Research problem within the HLUC_02_UCS_02 observes the Energy Service Provider (ESP) as the main subject and its CAPEX optimization goal. To optimize CAPEX, ESP needs to conduct optimal investments on RES and FlexAssets, both in term of siting and sizing. To do so, this research problem thoroughly investigates how different i) siting configurations, ii) sizing configurations, iii) characteristics of FlexAssets and iv) market interactions on various markets affect the overall CAPEX. The research problem should result with a business strategy (or even strategies) that minimizes CAPEX, while satisfying all other constraints, both of the technical and legislative nature. Figure 21 illustrates possibilities where ESPs may act. Wide palette of activities creates challenges, but also big opportunities to develop optimal business strategies that may result in very favourable end results, specifically in terms of this research problem – optimization of CAPEX. ESP’s possibilities to trade electricity on various markets (wholesale, reserve, *distribution level flexibility market*…) alongside with the FlexAssets (both existing ones and potential ones) and demand response contracts with or without network awareness present a “playground” for the purpose of this research problem. The art of the whole problem is to synchronize all the possible ESP’s activities in an optimal manner, while taking into consideration possible peculiarities that market regulations in some countries may possess. For instance, given the fact that ESP is not by definition also a DSO (but an profit-oriented entity independent from the DSO), network awareness is a topic that will be investigated, and proposals will be stated how to regulate it in some future market concepts. Exactly such dilemmas present a huge motivation for the research in scope of this use case scenario. Not only that the existing regulations will be incorporated in the model and the optimal business strategy developed, but recommendations how to enhance the market environment will also be formulated.

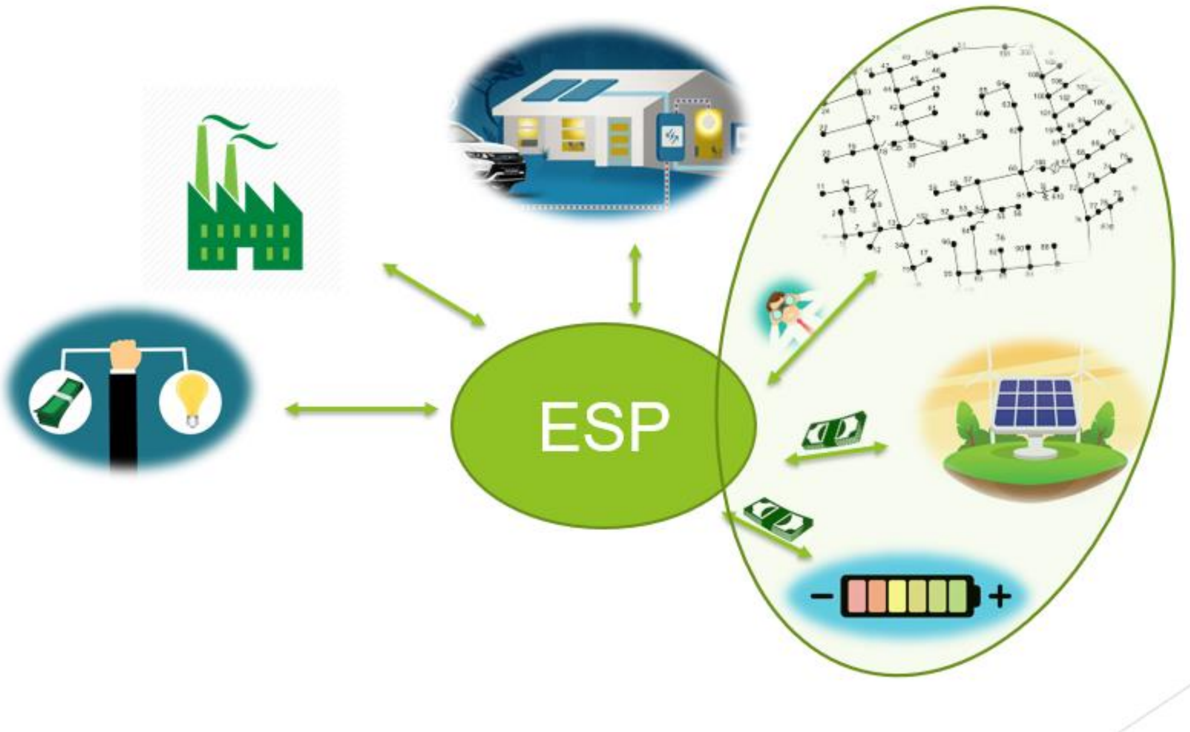

Figure 21: ESP's scope in HLUC_04_UCS_02

Novel FLEXGRID contributions follow the above-mentioned research motivation. One of the biggest impacts should be a holistic approach to the problem. Various electricity markets are taken into consideration, from the conventional ones as the day-ahead market, then reserve and balancing markets, to the potential *distribution level flexibility market (DLFM)*. Furthermore, detailed characteristics of the used FlexAssets are taken into consideration to exploit their complementarities in an optimal manner. In that way, detailed laboratory testing of the various types of batteries are being conducted to determine realistic charging and discharging characteristics and to enhance the precision of their lifetime expectancy prognosis. Important point of the whole problem present various forecasts. So, in the scope of the whole FLEXGRID project, great effort has been put on developing detailed and precise RES production, market (prices) and consumption forecast algorithms. All the above-mentioned present high-quality foundation for the holistic network-aware siting and sizing of RES and FlexAssets with the goal of ESP's CAPEX minimization. But, it is important to mention that network awareness needs to be taken with a pinch of salt, as various cases such as i) ESP is also a DSO (Badenova/bnNETZE), ii) DSO provides network data to the ESP, iii) ESP has no access to the network data will be examined. Efforts put in the research should result with the efficient exploitation of available instruments to ensure reliable energy supply with the lowest CAPEX possible.

4.2 Survey on related works in the international literature

The research problem in this chapter is consisted of multiple layers. In the center of interest is a profit-based ESP company that is searching for an optimal business strategy that minimizes CAPEX. To minimize CAPEX, OPEX also needs to be modelled and quantified. Thus, a literature survey has been conducted for the purpose this research problem.

There are various papers considering siting and sizing of the assets. Most of them consider solely energy storage systems with the first big distinction among them whether they observe the problem on the transmission [60]–[62] or distribution level [63]–[65] .

[60] 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 [61] 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 [62] 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 [63]. 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 [66], 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. [64] 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. [67]–[69]). 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 [70] 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 [71], it is has shown how the integration of DERs (when they are optimally located and sized) may help in reducing voltage deviation and power losses. [72] 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. An interesting article is also [73], where authors describe siting and sizing of concentrating solar power plant. Authors pointed out that improper size (and location) may not only result with high economic costs, but the plant could cause reverse power flow and voltage limit violations, which is all but the desirable scenario.

4.3 Basic system model to be followed

The main goal of the model developed as part of this use case scenario is to minimize ESP's CAPEX by optimally siting and sizing the FlexAssets under its management. To do so, various scenarios examine different siting and sizing solutions and consequently multiple OPEX models (according to the specific user preferences and technical constraints). Among available scenarios, the optimal one is selected according to the given constraints in such manner to site and size them for lifetime to operate in an optimal way. Following the strategy proposed in this model, ESP invests in RESs and ESSs to satisfy the demand in the least costly way.

As part of this use case scenario, an ESP is considered network-aware, which a lot resembles the situation in the Badenova/bnNETZE case. In a nutshell, two options are viable:

- DSO and ESP are practically one entity (Badenova/bnNETZE case)
- DSO gives ESP access to the network model in a prescribed way[2]

[2] By the term "access to the network model", we mean that the ESP's accessibility level to the underlying network data may vary according to the will of the DSO and/or the regulatory framework constraints. For example, if the DSO does not want to disclose critical information from its network infrastructure, an alternative

ESP is also considered to be energy supplier. Although that might not always be true, it adds great amount of complexity when aggregators are not suppliers, because their actions (may) cause imbalance to the suppliers.

Creating optimal investment strategy, as already mentioned, without any doubt requires detailed analysis of consequent OPEX scenarios for different siting and sizing possibilities. Moreover, for such approach, it is not enough to merely examine what effects newly installed FlexAssets bring in terms of capacity, but market interactions are also important factor to consider (mainly OPEX-related). Investments are made precisely in order to reduce the need for unfavourable transactions on the wholesale market to satisfy the demand and ensure system reliability and safety. To successfully encompass all above mentioned, the following modules from the FlexSupplier's Toolkit are used:

- Forecasting engine
- Optimal bidding algorithm
- FlexAsset sizing/siting algorithm
- Optimal scheduling algorithm

Although the main emphasis regarding CAPEX is on the FlexAsset sizing/siting algorithm, without the rest of the listed submodules, OPEX models, market interactions and completeness of the model in general wouldn't be accomplished.

The forecasting engine is used both explicitly for the investment decisions and to accommodate the daily operation modelling needs. Obviously, different future time horizons are used. Regarding investment decisions, longer (and less precise) horizon is used to predict future trends in terms of demand/production curves, wholesale prices etc. While shorter horizon forecasts, which tend to be more precise, are input parameters for the algorithms which handle daily operation of the FlexAssets under ESP's management.

The optimal bidding algorithm is used to model the interactions with various markets and the optimal scheduling algorithm to schedule the FlexAssets' operation, both of them achieving optimal solution while obeying a given set of constraints.

4.4 Basic problem formulation and algorithmic solutions

The model is formulated as a single-level problem. Objective function penalizes investment costs, leading to their minimization. Choosing between deterministic, stochastic or even robust (worst-case analysis) setup depends on the exact use of the algorithm. Perhaps further research in scope of this use case scenario will crystalize the most appropriate approach, but there is also a possibility to develop few options to accommodate specific needs of an ESP user, who will the project's FlexSupplier's Toolkit (FST). Prerequisite for a model to be realistic

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is to publish signals periodically in order for the interested ESPs to be able to infer (or else acquire an indirect knowledge) of the network status/condition.

and, thus, its results trustworthy, is a very precise and realistic mathematical formulation of the problem. So, the constraints play a very important role. They should on one hand represent reality as much as possible, but on the other hand they should be solvable in today's solvers. Here are mentioned the most important constraints concerning all the most relevant characteristics of the involved entities for the purpose of this research problem. ESP is in this use case scenario considered network-aware, so network constraints are included. This means that power flows, voltage deviations, power losses and possible congestions are modelled under the common network constraints. Subsequently, demand at all times should equal the sum of production and purchased quantities of electrical energy and losses. Next, an important part of the model is to present ESSs. Thus, great amount of effort is put into enhancing battery modelling through thorough laboratory battery charging/discharging and life expectancy (cycles) testing of different battery types and makes. Novel findings will be incorporated in the following constraints:

- Charging/discharging power limit
- Charging/discharging efficiency factors
- Charging/discharging curves
- Battery capacity (SOE) cannot exceed given limit

To precisely model load shifting and demand response services in general, it is important to include inflexible and flexible load demand curves, alongside with the RES production curves. Shiftable loads have the liberty of executing a specific task in a wider horizon, but the task still needs to be executed in a given timeframe. Furthermore, DR users may give the permission to the DR contractor to curtail some of the demanded power (not below some agreed boundary, under which would cause too much of inconvenience of the end-user). Constraints also include different market restrictions on which ESP places its bids and offers. According to the described problem and above-mentioned constraints, following should be mentioned as main variables of this use case research problem:

- FlexAsset capacity
- FlexAsset location
- SOE of ESS
- Charging/Discharging power of ESS
- Bids/Offers on different electricity markets

The most important parameters are:

- FlexAsset prices
    - ESS
    - RES
- Network characteristics
- ESS characteristics
- RES max. output
- Market prices
- RES production curves
- Consumption curves

4.5 Datasets to be used for simulation setup and most important KPIs

The following table summarizes the data to be used for simulation setup:

Table 4: Datasets to be used (tentative list) for HLUC_02_UCS_02

Hourly day-ahead energy market prices	Hourly active power production
Hourly balancing market prices	Hourly active power consumption
Price bids and capacity offers in the Reserve Market	ESS technical data sheet – energy/power rating, charging/discharging efficiencies
System's Upward/Downward reserve requirements by the TSO	Distribution Network data
Data (capacity and cost) of Flexibility Suppliers (DR aggregators, batteries, etc.)	ESS financial data sheet
RES financial data sheet	

The above-mentioned datasets include all the data needed for HLUC_02_02 concerning OPEX minimization in addition to the financial data of FlexAssets relevant for the investment decisions.

The most important KPIs may differ depending on which market is the ESP actor most concentrated on. One of the indicators is surely curtailment of the renewable energy sources. Should curtailment levels be high, this would clearly indicate inadequate dimensioning of the RES, and consequently not justifiable capital expenditure costs. Furthermore, multiple simulations will be done and then mutually compared to draw conclusions how each of the market influences the problem in general. In that manner, there will be simulations where only day-ahead energy market (DA-EM) is considered, then slowly building the model by adding other markets such as Reserve markets and Flexibility market proposed by the FLEXGRID project. The general assumption is that multiple markets introduce complementarity into the system and consequently more opportunities for the ESP to optimize its FlexAssets' utilization and increase their profit (/decrease their costs). Exactly KPIs such as curtailment of RES, ROI and overall profit will be clear indicators how the concept works.

The ESP's participation in multiple energy markets by adopting an optimal stacked revenue model is investigated in the use case scenario analyzed in chapter 5 below.

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

5.1 Research motivation and novel FLEXGRID contributions

Congestion management and frequency/voltage control issues caused by the high distributed RES penetration increase volatility of energy prices in various existing energy markets (e.g. day-ahead, intra-day, balancing, reserve markets at the transmission network level) as well as in the emerging local flexibility markets (e.g. Distribution Level Flexibility Markets - DLFMs proposed within FLEXGRID). This price volatility offers a potential for energy arbitrage (i.e. buy power when the price is low and sell it during high-price time periods) and respective revenues for ESPs, who own and invest in Energy Storage Systems (ESS).

In FLEXGRID use case scenario 2.3 (UCS 2.3), 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 forecasters, energy prosumption forecasters 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: 1) Day-Ahead Energy Market (DA-EM) operated by the MO, 2) Day-Ahead Reserve Market (DA-RM) operated by the TSO, 3) Day-Ahead Distribution-Level Flexibility Market (DA-DLFM) operated by a novel market entity called FMO, and 4) Balancing Market (BM) operated by the TSO.

The objective function of the ESP's problem is to maximize its aggregated profits from the four aforementioned markets. The novelty of the FLEXGRID's mathematical model and algorithmic approach is that the ESP co-optimizes its participation in various markets instead of simply participating in each of them individually in a sequential manner. As far as the day-ahead wholesale energy market is concerned, the ESP decides the BSUs' operation schedule by taking as input the nodal price, which corresponds to the node of the transmission grid at which the distribution network is connected. Secondly, the ESP makes profit by providing upward and downward reserves in the day-ahead reserve market. The upward/downward reserve prices are obtained from the reserve market clearing process and are the same throughout the transmission grid. Thirdly, the ESP participates in the day-ahead flexibility market by providing flexibility services to the DSO (i.e. active and reactive power (P-flexibility and Q-flexibility) based on nodal prices within the distribution network). Finally, the ESP participates in the near-real-time balancing market to balance its portfolio.

In light of the recent progress in the development of distribution level Flexibility Markets [74] FLEXGRID studies the operation and market behavior of an ESP (or else called Flexibility

Service Provider) owning a set of distributed BSUs and providing energy and ancillary services both to the TSO and the DSO. We assume that the ESP is acting as a price maker in the DA-RM and the DA-DLFM and a price taker in the DA-EM and near-real-time BM.

FLEXGRID's R&I novelties and contributions can be summarized as follows:

- FLEXGRID proposes a novel energy market architecture[3], in which a Reactive Distribution Level Flexibility Market is introduced in the timeframe between the DA-EM and the near-real-time BM. The DA-DLFM is operated by an independent FMO legal entity (such as NODES) and enables: i) DERs to participate in the transmission-level wholesale energy markets without jeopardizing the smooth operation of their underlying distribution network, and ii) DSO to buy the needed flexibility to tackle the possible contingencies resulting from the wholesale energy market dispatch decision.
- FLEXGRID proposes a stacked revenues business model for an ESP that owns distributed BSUs. In contrast to the relevant literature, FLEXGRID co-optimizes the operation and the bidding strategy of the BSUs' owner in both transmission-level and distribution-level markets. Bilevel mathematical modelling is used to model the decision process of the ESP.
- FLEXGRID solves a bilevel mathematical program converting it into an MPEC (Mathematical Program with Equilibrium Constraints) formulation through the KKT-based method [75]. Then, the non-linear MPEC is transformed into a MILP (Mixed Integer Linear Program). Since this work considers strategic participation in more than one market (DA-RM and DA-DLFM), it also uses the binary expansion method to deal with non-linearities.

To the best of the FLEXGRID consortium's 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. Various case studies will be investigated and system-level simulations will be derived using real-life datasets (as well as realistic synthetic data) based on FLEXGRID consortium's expertise.

5.2 Survey on related works in the international literature

Price volatility levels are expected to continuously increase in the coming years due to the increasing penetration of distributed RES generation. As a result, profit-based ESP companies may find attractive opportunities to optimally utilize their FlexAssets towards maximizing their business profits. In the international literature, there are two main categories for ESP's revenue modelling, namely price-taker and price-maker models.

In the context of the ESP's price taker models, authors in [76] analyze an optimal bidding strategy and [77] formulates a stochastic optimization problem for an ESS owner to maximize its energy arbitrage profit under uncertainty of market prices. In order to reduce the

[3] See more details about the proposed Reactive DLFM architecture in section 2.2.1 of FLEXGRID D2.2 here: https://flexgrid-project.eu/deliverables.html

computational burden that arises from stochastic optimization, [78] uses Information Gap Decision Theory (IGDT) to efficiently capture the market price uncertainty. In the context of ESP's price maker models, researchers in [37], [79]–[83] consider large, price-maker independently operated ESSs. [37], [79] and [82] considered a price maker ESS investor that owns and operates a number of geographically dispersed storage units at different transmission network buses and participates in the day-ahead electricity market. They used bilevel stochastic optimization models to optimize the private investor's offering/bidding strategy, which is transformed into a Mathematical Program with Equilibrium Constraints (MPEC). In the upper level the ESS's profits are maximized, while in the lower level a DC-OPF problem is solved, clearing the market. All these works that consider a price-maker ESSs assume that only the ESS players act strategically in the wholesale market.

Regarding the use of ESSs for an ESP's simultaneous participation in more than one market, there are several recent works in the international literature. In [34], an ESS is operated by an ESP to maximize stochastically its profit in both the energy and reserve markets. In [84], a commute EV aggregator is considered to participate in both the retail energy and the capacity-based frequency regulation markets. Authors in [85] investigated optimal bidding strategy for an ESS in the wholesale, the spinning reserve and the price-based frequency-regulation markets, while accounting for the battery degradation cost. [86] assumes a similar ESS-owning ESP business model, proposing a robust optimization approach to deal with uncertainties related to market prices and reserve deployment. [87] considers an ESS aggregator participating in the wholesale and regulation markets, while [88] proposes a joint optimization framework for ESSs to reduce energy bills of commercial consumers (peak shaving) and seek profit through the provision of frequency regulation services. In [89], a generic formulation of the scheduling problem of a multi-service ESS is provided. In [90], an ESS-owning ESP is considered that simultaneously participates in three markets (energy arbitrage, ancillary services and DSO's congestion market). Finally, [91] deals with the case of a price maker ESSs that adopts the stacked revenues' business model by participating in both Day-Ahead (energy and reserve) and Balancing Markets. The authors modelled a profit maximization problem of the ESS as a bilevel programming problem. In the upper-level problem the ESS seeks to maximize its expected revenues from all markets, while in the lower level the day-ahead market and the balancing market are cleared sequentially by solving two equivalent Economic Dispatch problems. Using the Karush-Kuhn-Tucker (KKT) conditions of the two lower-level problems, the bilevel program is transformed into an equivalent single-level optimization model, which is in fact an MPEC.

FLEXGRID elaborates on specific features from all the discussed and reviewed works and advances the state-of-the-art by considering a price-maker ESP entity that participates simultaneously in four markets.

5.3 System model and problem statement

In this UCS, FLEXGRID proposes a novel energy market architecture, in which the DA-DLFM follows the market clearing process of the distribution network-unaware day-ahead energy and reserve markets without changing the existing wholesale energy market structure. The DA-DLFM alters, if needed, the day-ahead energy market dispatch of the DERs participating in the transmission-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 Balancing Market (BM).

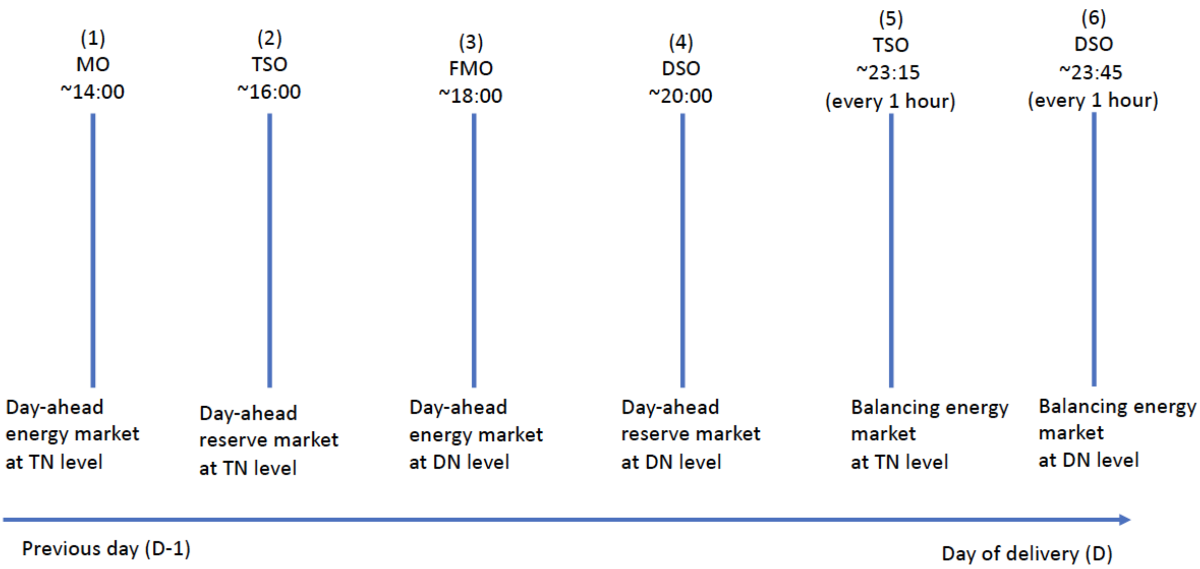

Figure 22: Sequence and timing of markets in FLEXGRID R-DLFM architecture

Table 5: Summary of markets assumed within FLEXGRID

Market #1	Market Operator (MO) operates the day-ahead energy market at the Transmission Network (TN) level
Input	Bids from all market participants and basic power flow constraints at the TN level
Output	Market clearing results (TN-aware day-ahead dispatch – energy quantity and price €/MWh per accepted market participant and node) → DN assumed as "copper plate"
Market #2	TSO operates the day-ahead reserve market at the TN level
Input	Bids from all market participants at the TN level + DAD schedules from MO + RES/demand forecasts + maintenance-related info from assets and grid
Output	Reserve market clearing results at the TN level (available power capacity reserved and price €/MW per accepted market participant)
Market #3	Flexibility Market Operator (FMO) operates the day-ahead energy market at the Distribution Network (DN) level
Input	Bids from all market participants at the DN level (incl. FlexAssets) + DAD schedule from MO at all TSO-DSO coupling points + DN topology constraints
Output	Market clearing results (DN-aware day-ahead dispatch – energy quantity and price €/MWh per accepted market participant and DN node)

Market #4	DSO operates the day-ahead reserve market at the DN level
Input	Bids from all market participants at the DN level + DAD schedules from FMO + local RES/demand forecasts + maintenance-related info (if any)
Output	Reserve market clearing results at the DN level (available power capacity reserved and price €/MW per accepted market participant)
Market #5	TSO operates the balancing energy market at the TN level
Input	Bids from all market participants at the TN level (incl. DER aggregators) + updated RES/demand forecasts + updated data from SCADA/EMS
Output	Balancing energy market clearing results at the TN level (i.e. Up/Down activation energy quantities and prices €/MWh per accepted market participant)
Market #6	DSO operates the balancing energy market at the DN level (only when DSO has a balancing responsibility for its DN operation)
Input	Bids from all market participants at the DN level + updated local RES/demand forecasts + updated data from Distribution Management System (DMS)
Output	Balancing energy market clearing results at the DN level (i.e. Up/Down activation energy quantities and prices €/MWh per accepted market participant)

In the basic R-DLFM model, the sequence and timing of the markets is the one described in the table above (i.e. 1 → 2 → 3 → 4 → 5 → 6). We consider that the FMO may run the day-ahead energy market at the DN level right after the respective TN-level market clearing results are available (i.e. approximately at 14:00). So, we may assume that all the DN-level market stakeholders can provide their FlexOffers until 17:00 (or so). Then, the FMO runs the DN-aware market clearing process and publishes the results at around 18:00 (or so). Then, the day-ahead reserve market at the DN level may run in a way that resembles the respective procedure at the TN-level[4]. This process may end up at 20:00 (or so), which means that DSO has contracted the required reserve units in order to deal with potential local congestion and voltage control problems at its DN. In case that the regulatory framework allows the DSO to have a balancing responsibility for its network (cf. shared responsibility model, in which the TSO and DSO share the balancing responsibility in each one's area of interest), then a balancing energy market at the DN level may also take place right after the TN-level balancing energy market. This market clearing process should be quick enough for the near-real-time dispatch schedule to be effectively communicated to all distributed market participants.

We consider the algorithmic steps of Reactive Distribution Level Flexibility Market (R-DLFM) architecture that have been extensively described in section 2.2.1 of FLEXGRID deliverable D2.2 [92]. The sequence and timing of markets in the R-DLFM architecture are illustrated in the Figure 22. The basic characteristic of the R-DLFM is that transmission network (TN) level

[4] See also novel re-dispatch regulatory framework that push towards innovative TSO-DSO coordination schemes (cf. German case): https://www.bmwi.de/Redaktion/EN/Publikationen/Studien/future-redispatch-procurement-in-germany.pdf?__blob=publicationFile&v=2

markets are cleared before the DN-level ones, so the three types of DLFMs operate reactively according to the market clearing results of the preceding TN-level markets. Without loss of generality, in this UCS, we consider only DA-DLFM (i.e. market #3) and not markets #4 and #6.

5.4 Problem formulation and algorithmic solution

A bilevel formulation is proposed for the ESP's problem to calculate its optimal bidding strategy and the charging/discharging schedule of the BSUs. In more detail, in the upper level, the ESP decides on the BSUs' operating schedule and its bidding strategy, while taking as input the day-ahead energy prices and balancing market forecasted prices and anticipating the impact of its decisions on the reserve (DA-RM) and flexibility markets (DA-DLFM). The ESP's decisions include the power traded to the day-ahead energy market, the price and quantity bids to the DA-RM and DA-DLFM and the power bought from/ sold to the near-real-time balancing market (BM). In the lower level, for given ESP's decisions, the TSO and the FMO clear the DA-RM and the DA-DLFM respectively. It is worth mentioning that in the DA-RM and the DA-DLFM clearing processes, the bids of the other market participants are treated as parameters. Finally, since the DA-DLFM follows the clearing process of the wholesale energy and reserve markets, the decisions of the latter, concerning the demand and production in the distribution network in which the ESP's BSUs are located, are also treated as input parameters to the lower-level DA-DLFM problem.

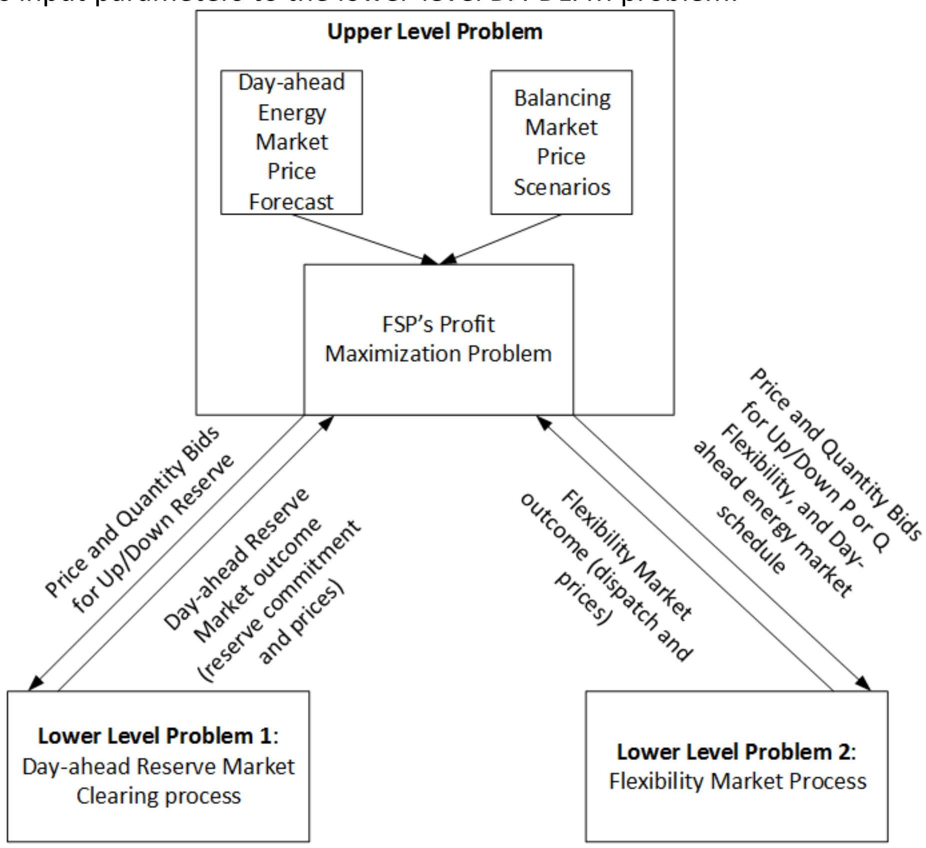

Figure 23 - Proposed bilevel model for FLEXGRID UCS 2.3

To mathematically formulate our problem, we need to model the following:

- Upper-level problem (i.e. ESP's profit maximization)
- Lower-level problem 1 (i.e. DA-RM clearing process)
- Lower-level problem 2 (i.e. DA-DLFM clearing process)

In the following subsections, we provide more detailed descriptions. Explicit mathematical notations and equations will be delivered in subsequent versions of this deliverable (i.e. D4.2 in month 18 and D4.3 in month 26).

5.4.1 Upper Level Problem: ESP's profit maximization

The objective function of the upper level (UL) problem maximizes the ESP's profits acquired from its participation in the various markets, through selecting the optimal bidding/offering decisions. As far as the DA-EM is concerned, the ESP decides on the BSUs' operation by taking as input the nodal price, which corresponds to the node of the transmission grid on which the distribution network connects with. Secondly, the FSP earns a profit by providing upward and downward reserve capacity in the DA-RM. The upward/downward reserve capacity prices are obtained from the DA-RM clearing process and are the same throughout the transmission grid. Thirdly, the ESP participates in the DA-DLFM, in which it gets paid for its flexibility services relevant with active and reactive power (P-flexibility and Q-flexibility) based on nodal prices that are calculated in the clearing process of the DA-DLFM. Finally, since we consider that the DA-DLFM follows the afore-mentioned wholesale energy and reserve markets (cf. R-DLFM model presented in the system model above), the active power DA-DLFM dispatch concerning the ESP's BSUs will trigger the ESP to re-adjust its energy market position by selling/buying power in the near-real-time Balancing Market. In contrast to the wholesale energy market prices, which can be predicted with relatively high accuracy, the Balancing Market prices are highly volatile and they are considered stochastic in the FLEXGRID models (see also figure above). We consider this uncertainty through a finite number of scenarios.

The ESP's profit maximization problem is subject to several constraints as follows:

- Discharged/charged power that is sold/purchased in the wholesale energy market is constrained by the inverter apparent power rating. A binary variable indicates the operating mode of the BSUs, being equal to 1 in discharge mode and to 0 in charge mode,
- the upward reserve capacity provision is constrained by the scheduled discharged/charged power that is traded in the energy market and the inverter apparent power rating,
- the downward reserve capacity provision is constrained by the power traded in the energy market and the BSUs' power rating,
- the (upward/downward) flexibility provision to the DSO is constrained by the BSUs' apparent power rating and the energy and reserve schedules,
- BSU's state of charge (SoC) related constraints,
- BSU's capability of upward/downward reserve capacity provisioning,

- the overall active/reactive power schedules of the BSUs should be calculated such that the apparent power at each timeslot does not exceed the apparent power rating,
- the Q-flexibility quantity bids of the BSUs are constrained, and
- flexibility market price bids should not be negative.

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

The Lower-Level Problem 1 represents the clearing process of the Reserve Market. We assume that the Day-Ahead Reserve Market (DA-RM) clearing is independent from the energy market and the participants submit capacity and price bids. The objective function of the lower-level optimization problem 1 minimizes the reserve capacity procurement cost based on the market participants' reserve price and capacity bids. Generators, DR aggregators and Energy Storage owners are considered as eligible market participants.

The objective function of the lower-level optimization problem 1 is subject to several constraints, namely: i) upward/downward reserve requirements (dual variables of these constraints result in reserve up and down prices), ii) limits for the up and down reserve provision of a generator, iii) limits for the up and down reserve provision of DR aggregators based on their respective capacity offers, iv) upward/downward reserve commitment concerning the ESP's BSUs cannot exceed its respective FlexOffers.

5.4.3 Lower-Level Problem 2: Day-Ahead Distribution Level Flexibility Market Clearing Process

The Lower-Level Problem 2 represents the clearing process of the DA-DLFM. Following the decision on energy dispatch and reserve capacity commitment, a Flexibility Market Operator (FMO) runs the DA-DLFM. The FMO's objective is to ensure the necessary active and reactive flexibility at the minimum cost to avoid local congestion problems and voltage violation issues. The ESPs offer their flexibility capacity and cost to the FMO via FlexOffers. The objective function of the Lower-Level Problem 2 minimizes the flexibility procurement cost.

The objective function of the lower level optimization problem 2 is subject to several constraints, namely: i) constraints related with P-flexibility and the Q-flexibility quantity offers of the ESP's competitors, ii) upward/downward P/Q-flexibility provision by the ESP's BSUs cannot exceed its respective quantity offers, iii) distribution network related constraints.

The nodal active/reactive flexibility prices come from the dual variables of the constraints. The active/reactive DLFM prices will be non-zero in case of distribution network contingencies, in order for the ESPs to be compensated for their P/Q-flexibility services required for the distribution network to operate within its technical limits (voltage and line thermal bounds). In case that the wholesale energy market schedules, concerning the local DERs, do not disturb the smooth operation of the distribution network, the DLFM prices will be zero.

5.4.4 Algorithmic solution method

The formulated bilevel problem can be solved as in [93] and [94]. First, we replace the two lower-level problems with their respective Karush-Kuhn-Tucker (KKT) conditions. Here, we should note that these KKT conditions are necessary and sufficient optimality conditions, since optimization problems are continuous and linear [95]. The resulting single non-linear optimization problem is a Mathematical Program with Equilibrium Constraints (MPEC). To solve it, we linearize the non-linearities in the complementarity conditions and the objective function. More mathematical details will be provided in a subsequent version of this report (D4.2).

5.5 Simulation setup and performance evaluation scenarios

To demonstrate the advantages of the proposed system, three main schemes will be implemented:

- **Scheme 1:** A price-maker ESP participates in all four markets in a sequential manner
- **Scheme 2:** A price-maker ESP participates in a subset of markets in a co-optimized manner implementing the proposed FLEXGRID methodology
- **Scheme 3**: A price-maker ESP participates in all four markets in a co-optimized manner implementing the proposed FLEXGRID methodology

Scheme 1 serves as benchmark to accurately quantify the gains of the proposed FLEXGRID scheme. Current state-of-the-art research works and existing commercial solutions for ESP's stacked revenue modeling deal with each market participation individually. Therefore, in scheme 1 we assume that the ESP makes an optimal bid in the DA-EM without considering the other three markets' operation. Then, the ESP continues by making an optimal bid in the DA-RM taking into account the DA-EM's results and without considering the other two markets' operation. Subsequently, based on the previous two markets' results, the ESP submits its optimal bid in the DA-DLFM without taking into account the BM's results. Then, the process ends by making a final optimal bid in the near-real-time BM.

Scheme 2 serves as one more benchmark in order to deal with the problem that there are no commercial distribution level flexibility markets at the time being. Hence, it is rational that an ESP cannot participate in a DLFM if it does not exist. There are also several EU countries, whose TSOs do not operate a near-real-time balancing market. As a result, by evaluating the performance of scheme 2, we will be able to quantify the ESP's profits in a today's realistic business context and thus realize whether the ESP's business can be sustainable (and in which specific market and network context).

Conclusively, via the proposed FLEXGRID scheme 3 we introduce a new DLFM from which the ESP can realize more revenues, while assisting the DSO to efficiently operate its distribution network under high RES penetration.

5.5.1 Simulation setup and data to be used

In order to setup a system-level simulation, we will use data for: i) historical market prices from day-ahead energy and balancing markets, ii) reserve market data, iii) distribution level flexibility market data, and iv) distribution network topology data.

Regarding historical market prices, we will use historical hourly day-ahead energy market prices, which are generally open in power exchanges such as Nord Pool [96]. Regarding historical hourly balancing market prices, we will use open data from Nord Pool as well as specific EU TSOs such as FinGrid [15]. Of course, it should be noted that the day-ahead and balancing market data should refer to the same geographical region.

As of DA-RM data, we will price bids (i.e. declared costs) and capacity offers of several participants in the DA-RM (i.e. FlexOffers). We will also use system's upward and downward reserve requirements by the TSO.

Regarding the DA-DLFM data, we will also use realistic FlexOffers from several ESPs/FlexSuppliers (i.e. capacity and cost). As there is no existing DLFM from real-life business, we will use realistic data according to NODES business expertise from several ongoing pilot/pre-commercial projects in several EU countries [97]. Moreover, we will also use hourly active power production of distributed generators and their power factors as well as hourly active power consumption of loads in the distribution network and their power factors. Finally, we will utilize distributed BSU data installed in a distribution network (i.e. energy/power rating, charging/discharging efficiencies, etc.).

For a given distribution network topology, we will also use data based on a realistic distribution grid representation such as the one shown in Figure 24[5]. Required datasets to be used in the AC-OPF model (or DistFlow model) described in 5.4.3 Lower-Level Problem 2: Day-Ahead Distribution Level Flexibility Market Clearing Process are (among others): i) distribution line admittance and capacity limits, ii) nodal voltage limits, iii) tap ratios, iv) shunt capacities, v) location of distributed RES/load/storage units, vi) capacity of distributed RES/load/storage units, vii) historical data of distributed RES/loads (at least 1-hour or 15-minute time granularity).

[5] It should be noted that the proposed FLEXGRID model will be tested and validated in several IEEE test systems such as 15-, 33-, 123-node system. We will also use real DN topology data from bnNETZE partner in Germany to validate the simulation results in the WP7 context.

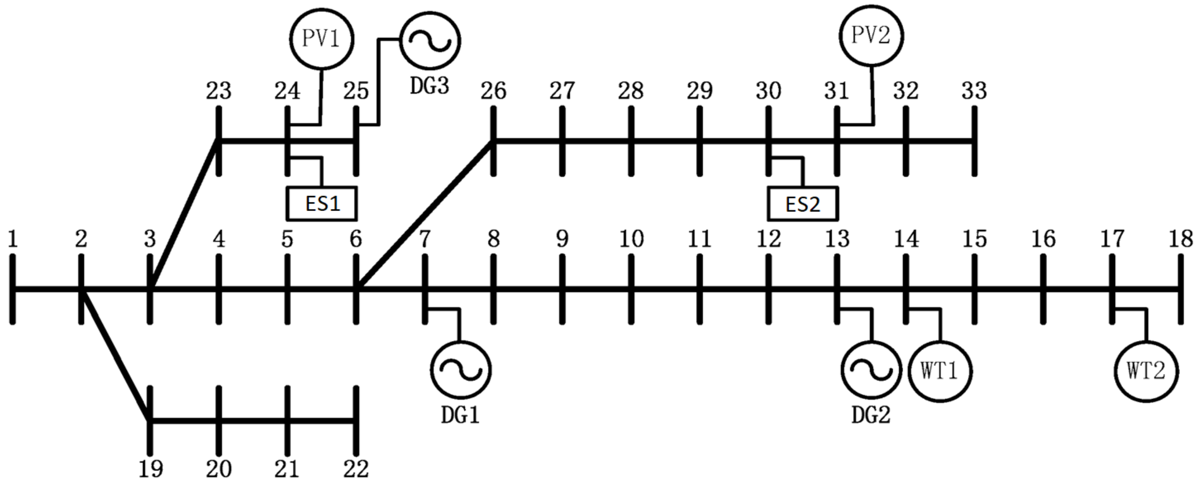

Figure 24: Example of a distribution network topology (IEEE-33 test system)

5.5.2 List of performance evaluation scenarios to be tested and validated

According to the above-mentioned simulation setup plan, the following performance evaluation scenarios (non-exhaustive list) will be tested and validated via system-level simulations at TRL 3 and will be integrated in the FlexSupplier's Toolkit (FST):

- Test various types of local congestion/voltage control problems in a given distribution network (cf. various levels of DA-DLFM price volatility)
- Test various levels of balancing market price volatility (cf. transmission-level problems)
- Test various distribution network setups (cf. "what-if" scenarios in which new FlexAssets are installed or a given set of FlexAssets are installed in other DN nodes)
- Test various types of market contexts (e.g. ESP's profit mix) in order to identify which market contexts are the most favorable for ESP's future FlexAsset investments
- Impact of ESP's FlexAsset portfolio size on DA-RM and DA-DLFM prices and ESP's profits

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

The following table summarizes the key performance indicators that will be measured to accurately quantify FLEXGRID's R&I added value. It should be noted that this added value will be further assessed both in scientific terms (i.e. excellence) and potential business impact terms. The results of this work will be fed into Task 8.2 dealing with impact analysis and innovation management.

Table 6: List of Key Performance Indicators (KPIs)

Actor	KPI	Description
ESP	Increased revenues/profits	Compare a price-maker ESP scheme for a given DN, market and ESP FlexAssets' portfolio and its participation in several markets.

	Reduced RES curtailment	Show that the proposed scheme can optimally schedule BSUs and thus avoid RES curtailment increasing thus ESP's revenues.
	FlexAsset benefit/cost ratio	Measure the financial benefit obtained from the energy sales referred to the cost of the BSU portfolio under investigation. The ratio should be applied to the total lifetime of the BSUs.
	RES dispatchability rate	Measure the amount of RES capacity that can be managed with total flexibility or else is fully dispatchable.
	ROI factor	Define the business context under which an ESP can achieve acceptable (in terms of years) return on its BSU investment.
DSO	Voltage deviations are acceptable	Evaluate how close to the nominal value the voltage is before and after ESP's strategic bidding and scheduling. The goal is to keep voltage within acceptable limits, while ESPs are free to act strategically in a liberalized market context.
	Reduced network investments	For a given future RES penetration level, the DSO can reduce the needed investments to keep its system within acceptable limits.
	Probabilistic SAI	Show that SAI-related metrics can be within the required limits, even in cases when ESPs act strategically.
Market Operator	Merit Order Effect (MOE)	Quantify the reduction of energy prices due to the use of RES and FlexAssets by profit-based ESPs
Flexibility Market Operator	Minimize cost of flexibility procurement	Evaluate the performance of the FLEXGRID's advanced market pricing mechanism (DA-DLFM).

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

6.1 Research motivation and novel FLEXGRID contributions

FLEXGRID's main research motivation lies in the effective interaction between efficient energy markets and electricity grid management systems in the context of very high RES penetration levels. In this type of business environment, modern Energy Service Providers (ESPs) need to: i) adopt imperfect market context - aware bidding strategies to maximize their profits, ii) respect the underlying network constraints, and iii) make decisions about the optimal mix of their heterogeneous flexibility assets as well as their optimal sizing, siting and operation. In FLEXGRID's use case scenario (UCS) 2.4, we develop advanced models and algorithms that factorize all the above. 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. This scenario perfectly fits BADENOVA's business and can also be applied in a MicroGrid (MG)/energy island concept. As a matter of fact, there are many profit-based Energy Service Providers throughout Europe (such as BADENOVA), which are closely collaborating with their local DSO. 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).

The utilization of heterogeneous flexibility assets (e.g. Energy Storage Systems – ESSs, Renewable Generators - RGs, Demand Side Management – DSM systems) can harmonize consumption with production and guarantee the efficiency and stability of smart grids. These flexibility assets (FlexAssets) can be categorized according to: i) their type of operation, ii) the impact that their size and network location have on the smart grid planning process, iii) the impact that their scheduling decisions have on optimally responding to dynamically changing network and market states, iv) other business logic issues, which are related to ESP's business strategy (e.g., risk hedging, Return on Investment – RoI models, strategic business plans, etc.). Hence, the optimal mix and joint management of heterogeneous FlexAssets placed in a given geographical area and belonging to a specific company's portfolio is not a trivial research problem.

In this landscape, traditional electric utilities are transforming into Energy Service Providers (ESPs) that: a) purchase energy from the wholesale energy market, b) sell energy through retail markets, and c) further ensure their financial sustainability through the aggregation of heterogeneous FlexAssets and the use of ESS. There are five key elements that designers of advanced and holistic business models for ESPs have to seriously take into account.

The first is the large-scale use of ESSs, which is expected to grow at a compound annual growth rate (CAGR) of approximately 24.38% during the forecast period of 2020–2025 according to [74]. Consequently, ESPs are keen on adopting or developing business models that are able to optimally schedule the ESSs' operation according to the energy markets' state to maximize their profits.

The second relates to the aggregation of distributed and flexible load resources [74] and their scheduling towards the ESP's optimal participation in the energy market(s). This process is well known in literature as Demand Side Management (DSM). In this context, modern ESPs have to design integrated schedulers and enable in this way the deep interaction between ESS and DSM towards competitive design of business models.

The third fundamental challenge is to derive models and algorithms that provide optimal orchestration of heterogeneous FlexAssets under the operational limits of a physical distribution network. In particular, high renewable generator (RG) penetration increases the challenges related to the local congestion and voltage control issues of the distribution grid. Thus, modern ESP business models have to take into account these constraints, which become much more vital in very high RES penetration contexts.

The fourth critical issue in the development of holistic business models relates to the ownership and/or management of RGs. An ESP must be able to optimize the use of its heterogeneous FlexAssets to optimize energy utilization from its own RGs. This would render the ESP more independent and more competitive.

The fifth key element is related to the optimal participation of an ESP in the liberalized energy markets. In this perspective, the ESP's decision process can be formulated through complementarity modeling [75] and more specifically as a bilevel problem, in which the upper-level problem represents the maximization of ESP's profits and the lower-level one represents the market clearing process that derives the Locational Marginal Prices (LMPs). Thus, a Mathematical Problem with Equilibrium Constraints (MPEC) is generated, which is ultimately transformed into a Mixed-Integer Linear Program (MILP). This model considers the ESP as a price maker entity that, in contrast to a price taker ESP, is able to anticipate the electricity market's reaction to its decisions (quantity/price bids) and affect the system's marginal price.

In a nutshell, the major contribution of FLEXGRID is a holistic and sophisticated ESP'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 Survey on related works in the international literature

The current status regarding the related research works 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).
- 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).
- Underlying network topology is not taken into account for modelling optimal bidding strategies (i.e. network-aware bidding feature).

A number of research works in the literature use bilevel programming and complementarity modeling to model decision-making process of strategic players in liberalized energy markets. Works in [98]–[104] deal with the strategic operation of a Generator Company (GenCo) in electricity pool markets. More specifically, authors in [98] formulate a bilevel model, in which a GenCo maximizes its profit in the upper level, while in the lower level a Market Operator (MO) clears the market by solving an Optimal Power Flow (OPF) problem. In [99], the profit maximization problem of a GenCo is formulated as an MPEC, which in [101] is transformed into a MILP through binary expansion. The binary expansion approach was presented in [102], which also modeled the uncertainty in rival GenCos' bids and system's load. In [100], a non-interior point algorithm is used in order to find the equilibrium in a Stackelberg Game between a GenCo and a MO, thus clearing the market on top of an AC power system model. The authors in [103] modeled a bilevel problem to study the strategic behavior of GenCos under two different pricing mechanisms in electricity markets, namely uniform and pay-as-bid. Finally, authors in [104] formulated an MPEC that studies the problem of a GenCo's strategic investment. The authors used Benders Decomposition to tackle scalability issues. Furthermore, [37], [62], [79], [81]–[83], [91] examine the strategic participation of a merchant ESS owner in an energy market. The authors in [37] formulate the profit-maximization problem of a strategic ESS owner participating in wholesale day-ahead market as a Mathematical Program with Primal and Dual Constraints (MPPDC). The study in [79] considers a price maker merchant ESS owner aiming to maximize its profits through the coordination of the operation of geographically dispersed ESSs. The authors in [81] propose a look-ahead technique to optimize ESS's operator bidding strategy in the wholesale day-ahead energy market considering the operation in the following day, too. The work in [82]studies the impact on the profits of a price maker ESS owner when ramp-up/down limits of generating units are considered in the market-clearing process. The optimal sizing of a price maker energy storage facility is studied in [83]. A stochastic bilevel problem is formulated and solved using Benders' decomposition to make it tractable. In addition, the same authors in [91] formulated an MPEC in order to study parallel participation of an ESS owner in both energy and reserve markets. In [62], the authors studied the problem of the optimal investment of a strategic ESS owner, taking into account the transmission capacity expansion plans of the TSO. For the case of strategic load serving entities (LSEs), [105] formulated an MPEC in order to investigate the strategic bidding of an LSE in day-ahead markets, while [106] expanded the previous study to co-optimize LSE's bidding strategy in both energy and reserve markets. Our FLEXGRID work differs from the previous works by considering a progressive electric utility as a strategic market player. More specifically, this work uses complementarity modeling to model the decision of an ESP, which controls a Virtual Power Plant (VPP) with multiple heterogeneous FlexAssets, while it must simultaneously satisfy the distribution network constraints.

There is a great deal of studies dealing with the scheduling and bidding problem of a price taker ESP that is in control of a VPP. A VPP comprises of distributed generators, ESSs, flexible and inflexible loads. The work in [107] studied the problem of optimal bidding in the day-ahead and real-time markets of an EV aggregator, while [108] dealt with the bidding problem of a microgrid aggregator in the day-ahead market. The aggregator's objective is profit maximization without sacrificing its users' thermal comfort. The problem studied in [40] is the real-time scheduling of a microgrid composed of an RG, an ESS and an aggregated load, in order to minimize its electricity costs. The authors in [109] used robust optimization for the bidding problem of a VPP (in both day-ahead and real-time market) in order to tackle the challenges arising from uncertainties pertaining to: market prices, load variation and renewable production. For the same problem, [110] and [111] formulated hybrid stochastic/robust optimization models. Works in [112] and [113] studied the optimal scheduling and market participation problem of a VPP in day-ahead and real-time market, while ensuring the reliable operation of distribution network by incorporating technical network constraints into their models. The aforementioned works, [40], [107]–[113], considered price taker ESPs in contrast with our current work, which studies the optimal bidding and scheduling problem of a price maker ESP controlling a VPP with multiple heterogeneous FlexAssets.

6.3 System model and problem statement

We consider a transmission grid characterized by a set of buses and a set of transmission lines. 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. Renewable generators, ESSs, flexible (shiftable) and inflexible loads are located in each DN turning it into a Virtual Power Plant (VPP), which can supply/draw power to/from the rest of the grid. More specifically, the DN connected to a given bus is characterized by a set of nodes (DN buses), a set of edges (DN branches), a set of ESSs, a set of renewable generators, a set of shiftable loads and a set of inflexible loads. The ESP is responsible for controlling the ESSs and the deferrable loads to strategically participate in the given market (e.g. day-ahead, balancing, flexibility market) and maximize its profits. In addition, the ESP has to ensure the reliable and stable operation of DNs. The goal of this UCS is to calculate the ESP's optimal bidding strategy for participation in a given market and the optimal schedule of the heterogeneous FlexAssets, while simultaneously taking into account the distribution network constraints.

Ideally, the objective of the ESP is to use all its available local RES and thus avoid RES spillage. In addition, if the energy that the local RES produce is smaller than local demand, ESP may buy energy from the main grid at the lowest possible cost. At the same time, the ESP has to ensure the reliable operation of its network, which is a quite difficult task especially in high RES penetration scenarios, where local RES curtailment should be kept at a minimum. For example, as shown in the figure below, a congestion problem may occur due to a weak connection linking the DN with the main grid. Moreover, at the DN's edges, it is highly probable that various local voltage and congestion problems may occur frequently due to the expected high RES penetration and the rather weak connections within the local DN[6]. The goal of FLEXGRID's research work is to calculate the ESP's optimal bidding strategy in the day-ahead energy market and the optimal schedule of the FlexAssets, while simultaneously considering the distribution network constraints.

The proposed system model could also be applicable to energy communities, cooperatives (i.e. RESCOOPs [114]), islands and municipal/local electric utilities, which own local RES, local FlexAssets and operate the local DN at the same time. In these cases, it is essential to facilitate local and bottom-up RES and FlexAsset investments, which strengthen the energy autonomy and have lower costs in the long term. This is because investments in stronger interconnection points with the main grid or local network reinforcements have higher financial cost and/or very high uncertainty due to bureaucratic procedures.

In order to adequately present advantages of the proposed business model, we evaluate two main RES penetration scenarios (see more details in 6.5 Simulation setup and performance evaluation scenarios below). The first is the high RES penetration scenario. Its objective is to eliminate local RES curtailment and achieve at the same time network feasibility (i.e. satisfy the constraints of the distribution network). Thus, this case is dedicated in evaluating the network-aware bidding feature of the proposed model. On the second scenario, where RES penetration is low, we assume that demand cannot be satisfied by local RES, which is closer to what is happening nowadays. Thus, this case is dedicated in evaluating the market-aware bidding feature of the proposed model to minimize energy costs. Both network- and market-aware bidding properties of the proposed framework are formulated below.

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[6] By the term "weak distribution network connections", we mean that given the assumed very high RES penetration scenarios that we simulate, the DN may face local congestion and voltage control issues rather frequently. Nowadays, this type of problems may occur just a few times within a whole year, but this is not expected to be the case in the 2030+ era.

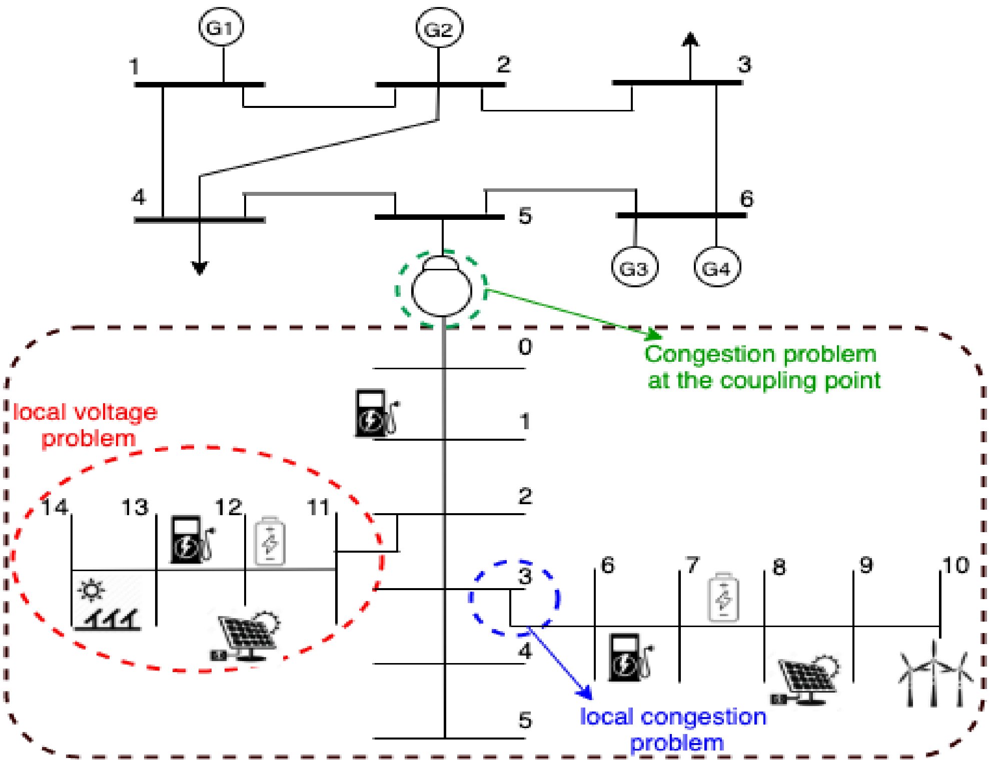

Figure 25: System Model

6.4 Problem formulation and proposed algorithmic solution

In order to mathematically formulate our problem, we need to model the following:

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

In the following subsections, we further provide more detailed descriptions. Explicit mathematical notations and equations will be delivered in subsequent versions of this deliverable (i.e. D4.2 and D4.3 in month 18 and month 26 respectively).

6.4.1 Modeling of Energy Storage Systems (ESS)

The ESP manages the ESSs' charging/discharging schedules. At each distribution network (cf. spatial arbitrage) and timeslot (cf. temporal arbitrage), each ESS (physical or virtual through the aggregation of several distributed battery systems) should be charged or discharged. Charging (or discharging) power is limited by the ESS' maximum charging (or discharging) rate. Thus, there is a binary variable indicating the operating status of each distribution network's ESS at each timeslot (e.g. the variable's value equals to 1, when an ESS is discharged and equals to 0 when it is charged). We assume a scheduling horizon of several time steps ahead. Without loss of generality, for the purpose of this FLEXGRID UCS, we assume 24-hour resolution for the ESP's day-ahead market participation. We also assume that the State of Charge (SOC) of each ESS cannot exceed the lower and the upper bound, while the final SOC of each ESS at the end of each day is considered equal to the first SOC of the next day. Finally, we assume discharge and charge efficiency factors, which represent the amount of energy that is lost during the charging/discharging operations. Conclusively, the ESP tries to charge more energy in timeslots when the price is low and discharge more energy in timeslots when the price is high. The ESS schedule should also be co-optimized with the ESP portfolio's renewable generation as well as the energy consumption.

6.4.2 Modeling of shiftable and curtailable loads (DSM units)

Shiftable and curtailable loads (or else Demand Side Management – DSM units) is the second type of FlexAssets that the ESP may use in order to optimally schedule its portfolio. Each shiftable load must fulfill a specific task within the scheduling horizon, meaning that a certain amount of energy must be consumed by a given DSM unit in that period. Every shiftable load also has a desired time schedule within which the operation must take place. Outside this desired time interval, the power consumption of this DSM unit is zero, while inside, it has an upper limit on its consumption rate. In addition to shiftable loads, the ESP may also curtail some load in case that the end user's convenience level does not fall below a pre-determined threshold. An example of curtailable load is an HVAC, whose temperature level may be set one degree ^{o}C below/above the pre-defined levels. This would mean that the ESP could realize more revenues without causing unacceptable discomfort to the end user. Conclusively, the ESP tries to consume more in timeslots when the price is low and consume less in timeslots when the price is high. Of course, the ESP portfolio's energy consumption should be co-optimized with the renewable energy generation and the available ESS capacity.

6.4.3 Modeling of the underlying Distribution Network (DN)

The scheduling decisions made by the ESP, which have been sententiously described above, must satisfy the distribution network's power flow constraints. In order to model the distribution network, we use the widely used by the literature linearized DistFlow equations from [115]. As a matter of fact, several high-quality research works that have recently been published in top-notch scientific journals such as [104] [105] and [108]use this linearized DistFlow equations. Within FLEXGRID WP5 research work context, we also derive AC-OPF models for the distribution network operation, which are more accurate and can better deal with RES uncertainties. In this DN's modeling, we model the active and reactive power flowing in all connecting nodes. We also model the active powers of flexible loads, inflexible loads and renewable generator in each node of the DN. Furthermore, we model the DN's physical constraints like line admittance, line capacity limits (MVA), nodal voltage limits, tap ratios, shunt capacities, etc. More mathematical details will be provided in D4.2 (Month 18).

6.4.4 Modeling of ESP's offers/bids

We assume nodal wholesale electricity market in which the ESP has to optimally choose for each DN and time step its energy offers/bids. The latter are limited by each DN's total power net capacity. There is a maximum quantity offer and bid that the ESP can submit at a given timeslot. Quantity offers/bids are also limited by the active power capacity of the coupling point between each DN and the transmission grid. Finally, Finally, the ESP decides on the optimal price bid that it submits to the day-ahead market in each time step (i.e. 24-hourly resolution is considered). For all the above-mentioned modeling, we assume that the ESP has distribution network topology data provided by the local DSO. The latter provides access to these datasets because it is also interested to keep its DN operation within acceptable network reliability limits.

6.4.5 Modeling the ESP's profit maximization problem

To schedule its heterogeneous FlexAssets in a network-aware and cost-effective manner, the ESP maximizes its profits that result from its participation in the day-ahead electricity pool market. When a DN located at a given bus supplies power to the grid (i.e. at the TSO-DSO coupling point) at a given timeslot, it sells this power in the pool market at a given price, which is the nodal price at this given bus. In contrast, when a DN draws power from the grid, it buys that power from the pool market at another given price. Hence, the ESP, given the production of the Renewable Generators (RGs) and the inflexible loads that must operate at any cost, decides on the quantity and price offers/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. More details about the mathematical model together with respective mathematical notations will be provided in D4.2.

6.4.6 Modeling the day-ahead wholesale energy market clearing process

A nodal transmission-constrained electricity pool market is considered. Apart from the ESP, generators and demand aggregators participate in this market. We assume the set of transmission grid buses, in which generators are located and the set of buses where demand loads are located. We consider a Market Operator (MO) entity, which tries to maximize the Social Welfare (SW) by considering: 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 ESPs) by solving a DC-OPF problem at the transmission network level. In other words, the objective of the MO is to minimize the social cost, i.e. the cost of energy production minus the willingness of demand aggregators to pay for that energy. The decision variables of MO's optimization problem are: i) the power supply of each generator, ii) the power consumption of each demand aggregator, iii) the power supply/consumption of each DN, and iv) the voltage phase angles at all buses at every timeslot. There should be an equation that expresses the power balance at each bus of the power grid at the transmission network level. The dual variables of these constraints provide the Locational Marginal Prices (LMPs). There are several more constraints in the DC-OPF problem, namely: i) the admittance of transmission lines, ii) generators' minimum and maximum capacity, iii) generators' ramp up and ramp down constraints, iv) demand loads' upper and lower bounds, v) transmission line capacity limits, etc.

6.4.7 Algorithmic solution method

ESP does not simply act as a price taker, but is able to anticipate the electricity market's reaction to its decisions (quantity/price offers). 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 (i.e. ESP's profit maximization as described in 6.4.5 Modeling the ESP's profit maximization problem) is constrained by the Lower Level Problem (i.e. maximization of social welfare as described in 6.4.6 Modeling the day-ahead wholesale energy market clearing process).

The formulated problem has a bilevel structure and has to be converted into a single optimization problem in order to be solved using a commercial solver. Thus, we follow the same procedure as in [77], [116]. In our bilevel optimization problem, the constraining Lower Level problem is a Linear Program and therefore, Slater's condition holds [95]. Thus, DC-OPF problem's Karush-Kuhn-Tucker (KKT) conditions are necessary and sufficient optimality conditions (i.e. satisfy convexity and constraint qualification). Therefore, solving the DC-OPF is equivalent to solving its KKT conditions, which is a non-linear system of equations. As a result, the lower level problem is converted into a set of non-linear constraints of the upper level problem, and our problem becomes a single Mixed Integer Non-Linear Problem (MINLP). The non-linearities coming from the complementarity conditions (subset of KKT conditions) are tackled using the Big-M linearization [117]. The non-linearities in the objective function are linearized using the Strong Duality Theorem applied to the lower level problem. Finally, the initial bilevel problem is transformed into an equivalent single Mixed Integer Linear Problem (MILP), which can be easily solved using a commercial MILP solver. The exact mathematical notations and equations will be provided in D4.2 (Month 18).

6.5 Simulation setup and performance evaluation scenarios

To demonstrate the advantages of the proposed system, three main schemes will be implemented:

- **Scheme 1:** ESP acts as a price taker taking into account DN physical constraints
- **Scheme 2:** ESP acts as a price maker without taking into account the DN physical constraints
- **Scheme 3**: ESP acts as a price maker taking into account DN constraints and implementing the proposed FLEXGRID methodology.

Schemes 1 and 2 serve as benchmarks that accurately quantify gains of the proposed FLEXGRID scheme (i.e. scheme 3). We use the business experience of BADENOVA in Germany. Nowadays, ESPs (like BADENOVA) only act as price takers, because they do not have the intelligence to optimally schedule their FlexAssets' portfolio and make optimal FlexOffers in the market. Moreover, ESPs do not consider DN constraints, because the current distributed RES penetration is rather small and the DN infrastructure is quite over-provisioned and periodically reinforced with new capacity/lines in order to ensure system reliability. Conclusively, FLEXGRID proposes an alternative solution (i.e. scheme 3), which is totally in line with the new EC directives about the use of flexibility at the distribution network level aiming at lowering social cost and incentivizing clean energy investments (i.e. installation of new FlexAssets and phase-out of conventional energy generators) [118].

6.5.1 Simulation setup and data to be used

To set up a system-level simulation, we will use data based on a realistic transmission grid representation such as the one shown in the figure below. Required datasets to be used for the DC-OPF described in 6.4.6 Modeling the day-ahead wholesale energy market clearing process are (among others): i) transmission line admittance and capacity limits, ii) voltage limits per transmission node, iii) tap ratios, iv) shunt capacities, v) conventional generators' technical characteristics (e.g. capability curves, ramp up/down, start up/down costs, minimum up/down times, generator's cost curves), vi) large RES (PV/wind) parks' location on the transmission grid, capacity and historical data (at least 1-hour or 15-minute time granularity), vii) large loads connected to the transmission grid, viii) historical load/generation data per substation at each TSO-DSO coupling point, ix) energy and power capacity of large storage units connected to the transmission grid.

For each distribution network, we will also use data based on a realistic distribution grid representation such as the one shown in Figure 25. Required datasets to be used for the AC-OPF model (or DistFlow model) described in 6.4.3 Modeling of the underlying Distribution Network (DN) are (among others): i) distribution line admittance and capacity limits, ii) nodal voltage limits, iii) tap ratios, iv) shunt capacities, v) location of distributed RES/load/storage units, vi) capacity of distributed RES/load/storage units, vii) historical data of distributed RES/loads (at least 1-hour or 15-minute time granularity).

Regarding the wholesale day-ahead energy market, we will use: i) historical market prices data (e.g. Nord Pool and other power exchanges), ii) market historical bidding curves of large generators, large RES units, large storage units, demand aggregators (quantity vs. cost curves), iii) reserve requirements (up/down limits), iv) historical weather data.

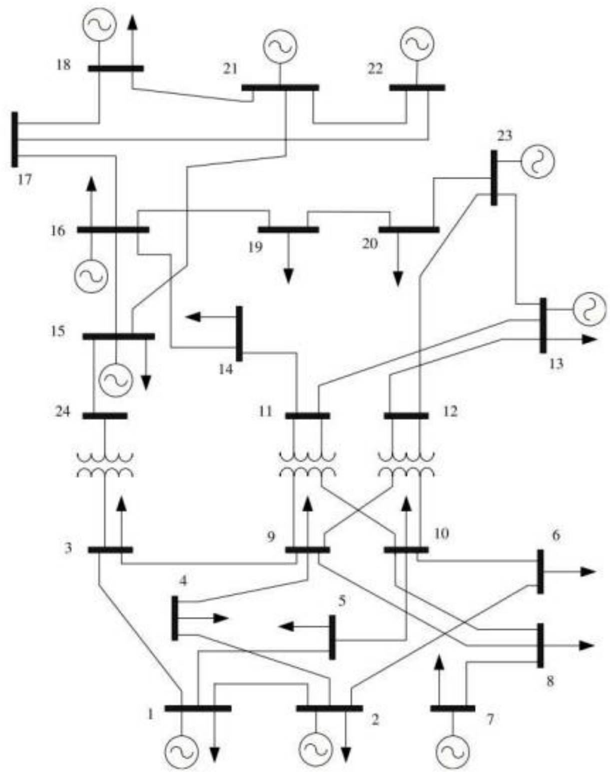

Figure 26: Example of an IEEE One-Area Reliability Test System [112]

6.5.2 List of performance evaluation scenarios to be tested and validated

According to the above-mentioned simulation setup plan, the following performance evaluation scenarios will be tested and validated via system-level simulations at TRL 3 (i.e. non-exhaustive list):

- ESP controls FlexAssets in a single distribution network (temporal arbitrage)
- ESP controls FlexAssets in multiple distribution networks (spatio-temporal arbitrage)
- High distributed RES penetration scenario (DN injects power to the transmission grid)
- Low distributed RES penetration scenario (DN draws power from the transmission grid)
- Impact of heterogeneous FlexAssets' siting (where to install new FlexAssets)
- Impact of heterogeneous FlexAssets' sizing (how much capacity of new FlexAssets to install)

For each performance evaluation scenario, more details are provided in the following subsections.

6.5.3 ESP controls FlexAssets in a single distribution network (temporal arbitrage)

In this performance evaluation scenario, our goal is to test our proposed scheme's capability to optimally schedule the ESP's FlexAssets in a given distribution network topology. Thus, the temporal arbitrage property of the proposed FLEXGRID scheme will be tested and validated. Moreover, the proposed scheme will be compared with the benchmark schemes 1 and 2 mentioned above in order to evaluate and accurately quantify the gains in terms of ESP's revenues/profits.

6.5.4 ESP controls FlexAssets in multiple distribution networks (spatio-temporal arbitrage)

In this scenario, our goal is to elaborate on the previous temporal arbitrage testing by considering the business case that the ESP FlexAssets' portfolio lies in several distribution networks. Therefore, the spatio-temporal arbitrage property of the proposed FLEXGRID scheme will be tested and validated.

6.5.5 High distributed RES penetration scenario (DN injects power to the transmission grid)

This scenario considers a medium to long-term future context, in which the ESP will be required to make optimal RES and FlexAsset investments in order to maximize local RES usage (or else minimize local RES spillage). Thus, in this scenario, we test and validate the network-aware bidding property of our proposed scheme to maximize local RES and FlexAsset usage. Our objective is to eliminate (or at least minimize) local RES curtailment and achieve at the same time network feasibility (i.e. satisfy the constraints of the distribution network).

6.5.6 Low distributed RES penetration scenario (DN draws power from the transmission grid)

In contrast to the previous scenario, this one considers a shorter-term future context, where RES penetration is still relatively low, and thus we assume that the local demand cannot be satisfied by local RES. We also assume that there are just a few times within a year that the distribution network may face potential congestion and voltage-related problems. Therefore, in this scenario, we test and validate the market-aware bidding property of our proposed scheme to minimize ESP's energy costs.

6.5.7 Impact of heterogeneous FlexAssets' locations

In this performance evaluation scenario, our goal is to "play around" with an exhaustive list of "what-if" simulation cases trying to accurately quantify the financial impact of the ESP's decisions to install renewable generators, ESS and DSM units at specific locations (i.e. nodes) of the distribution network. The result of our analysis will be to define optimal mix of heterogeneous FlexAssets' siting in order to both maximize ESP's revenues and not incur local congestion and voltage-related problems to the underlying distribution network.

6.5.8 Impact of heterogeneous FlexAssets' capacities

Elaborating on the analysis of the impact of heterogeneous FlexAssets' siting, we now study the impact of the aggregate size of renewable generation, storage capacity and flexible loads on the results obtained. More specifically, for a given optimal FlexAsset siting case, we evaluate the impact of each type of FlexAsset's capacity in the ESP's profits as well as the distribution system's operation. Thus, our goal is to avoid over-investments in FlexAssets and also to figure out what is the Return-On-Investment (ROI) factor for every new ESP's investment decision on FlexAssets in the short-term.

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

The following table summarizes the key performance indicators that will be measured in order to accurately quantify the FLEXGRID's R&I added value. It should be noted that this added value will be further assessed both in scientific terms (i.e. excellence) and potential business impact terms. The results of this work will be fed into Task 8.2 dealing with impact analysis and innovation management.

Table 7: List of Key Performance Indicators (KPIs)

Actor	KPI	Description
ESP	Increased revenues/profits	Compare price-maker vs. price-taker ESP scheme for a given DN, market and ESP FlexAssets' portfolio.
	Reduced RES curtailment	Show that the proposed scheme can optimally schedule FlexAssets and thus avoid RES curtailment increasing thus ESP's revenues.
	FlexAsset benefit/cost ratio	Quantify the financial benefit from the energy sales with respect to the cost of the FlexAsset under study. The ratio should be applied to the total lifetime of the FlexAsset.
	RES dispatchability rate	Determine the amount of RES capacity that can be managed with total flexibility or else is fully dispatchable.
	ROI factor	Define the business context under which an ESP can achieve acceptable (in terms of years) return on its FlexAsset investment.
DSO	Reduction of local congestion	Reduction of congestion in specific DN lines before and after FLEXGRID R&I. Decrease the number of congestion events in a specific area and minimize the probability of new congestion events in future higher RES penetration cases.
	Reduction of voltage deviations	Evaluate how close to the nominal value the voltage is before and after FLEXGRID R&I. Evaluate the impact in future higher RES penetration scenarios.
	Increased RES hosting capacity	For a given DN topology, FLEXGRID can increase the RES hosting capacity without incurring any problems to the DSO.
	Increased hosting capacity for EVs and other new loads	For a given DN topology, FLEXGRID can increase the new loads' hosting capacity without incurring any problems to the DSO (up to a threshold).
	Increased RES content	For a given DN topology, FLEXGRID can increase the RES content injected in the grid without incurring any problems to the DSO (up to a threshold).
	Probabilistic SAI	Show that SAI-related metrics can be within the required limits, even in high RES penetration cases.

	Reduced network investments	For a given future RES penetration level, the DSO can reduce the needed investments to keep its system within acceptable limits.
Market Operator	Merit Order Effect (MOE)	Quantify the reduction of energy prices due to various future RES penetration levels.
	Improved market competitiveness	Improve competitiveness of the electricity market, by providing energy and ancillary services to the grid at affordable costs, which will translate in increased welfare for the end users.
	Reduced energy cost for end prosumers	Quantify the effect of the ESP's optimal scheduling on the energy cost for each end prosumer.

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

7.1 Research motivation and novel FLEXGRID contributions

Modern power systems are facing tremendous changes in ongoing transformation from the conventional hierarchy towards new paradigm. This evolution is motivated by numerous reasons (some of them mutually dependent), following may be regarded as the most important ones:

- Political reasons
- Ecological awareness
- Economic reasons
- Technology enhancements
- Free-market (invisible) mechanisms

Among the biggest changes, one could emphasize high RES penetration which brings intermittency and uncertainty into the system, moving away from the conventional energy sources, more active role of consumers (prosumers), growth in importance of DERs, bi-directional power flow and utilization of various energy storage technologies and strategies. It is precisely energy storage systems that play a big role in securing stable and secure power supply in high RES energy mix share. With their temporal arbitrage ability, it is possible to store energy in times of its excessive production and use it when demand outweighs the output from RESs. Temporal arbitrage is, of course, used also in a more profit-oriented way where profit oriented stakeholder use energy storage to profit from the fluctuating prices on various energy markets (e.g.: [119]–[122]). Advancements in energy storage technologies and price decline have made storage accessible to wider community, even individual users. But energy storage prices (per capacity and/or power) still present quite a financial burden for investors, so many projects with high potential and added value may be postponed or cancelled due to the poor results of the cost benefit analysis (CBA).

To lighten high capital-intensive projects and to stimulate projects that are not even in consideration with current storage prices, the idea of this use case is to propose concepts and ideas where storage (capacity and power) may be leased for an agreed period of time. Reading above stated introductory lines, it might be obvious that the motivation for this research is manifold. From lowering power market financial entry barriers for interested players, developing innovative business models to greater (and presumably more efficient) utilization of the energy storage systems.

The FLEXGRID novelty lies in the concept of leasing a given energy storage asset/portfolio, which may generate many new business strategies and give boost to the modern electricity market paradigm. Concepts introduced in the further text will be characterized with the fact that the interested party has the opportunity to lease energy storage system (its capacity and power) instead of buying it. Although somewhat similar ideas may be found in the academic literature, this area of research is still pretty unexplored and there is room for lots of ideas and further research, innovation and discussion.

7.2 Survey on related works in the international literature

Literature covering business models based on storage lease strategies exists, but it is not as extensive as some other topic, thus it is fair to conclude that this topic has not yet been the main subject of interest in the academic (and presumably commercial) community.

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 [123]. 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. [124]. 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.

The listing series of articles introducing cloud energy storage model starts with the one from Liu et al. [125]. Similar to the concepts that will be presented in the scope of this research problem, the authors proposed a model where centralized storage facilities, owned by facility operator, provide decentralized energy storage services to the interested parties. In such a manner, the facility operator uses advantages of the economies of scale, and also it is far easier for a single storage owner to (primarily physically) manage his assets when they are on one place (centralized), rather than on multiple locations (decentralized). Along the article, it is more than once mentioned that motivation for such approach comes 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

Similar concepts are already used by profit-oriented companies. Green2store 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 installs batteries on users’ location but ordinates them in a centralized fashion. [126] is based on the previous article, it divides the services into energy capacity lease and power lease. Furthermore, it shows how such model could help in reducing overall electricity bill for user (e.g. avoiding peak prices). Motyka and other co-authors in [127] present a concept where distribution companies own storage and lease the capacity of the batteries to the customers for a certain fee. In addition to that, DSO may cover consumption at the time of non-production of renewable resources with the batteries, thereby reducing transmission losses and minimizing consumption peaks. Authors state that the main issue is the correct setting of the capacity of the batteries in the given node. Regarding CES concept, He et al. have proposed a bilevel model for optimal energy storage capacity pricing and sizing in [128]. In the upper-level, the CES operator makes capacity pricing and sizing decision, while the lower level simulates the renting and operating decision of consumers. Bilevel problems are generally hard to solve but as, in this case, only one variable of the upper level, namely the renting price, is used as a parameter in the lower level, so the authors propose a one-dimensional searching algorithm to efficiently solve the problem. A case study on 100 household consumers in Ireland has demonstrated that the CES concept is an effective business model. Emphasizing that the social return on annual investment increases about 69% in CES. The sensitivity analysis has showed that the net profit and sized capacity of CES increase with the decrease of unit capacity storage capital cost while the social return on annual investment stays near 70%. The net profit and sized capacity of CES decrease with the decrease of peak-valley price margin while the social return on annual investment increases. Authors in [129] further expanded the series of articles regarding CES, using perfect and imperfect information models to evaluate the behaviour of CES participants under those two information model types. The case study based on actual Irish consumer load profiles and prices has showed 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

In [130], through a two-stage optimization problem, the interaction between storage aggregator and users is formulated. 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.

Somewhat different concept is one called Virtual Energy Storage System (VESS). It is a storage analogue to the Virtual Power Plant (VPP). The authors in [131] explain how VESS aggregates various controllable components of energy systems, from conventional energy storage systems, flexible loads, distributed generators, microgrids, local DC networks to multi-vector energy systems. Aggregated entities act on a market as a single unit with specific characteristics, thus even smaller players have access to the wholesale market. More specifically, authors have showed in the article how VESS formed of domestic refrigerators and Flywheel Energy Storage System may be utilized for power system frequency response, having in mind how to minimize charging/discharging cycles of each unit in order to prolong their lifetime as much as possible. In similar manner, [132] a virtual electrical and thermal energy storage system is constructed using EV charging stations and buildings. The authors than propose an optimal scheduling method that takes virtual energy systems into consideration too. Researcher are proposing various utilizations of VES concept. To strengthen that claim in addition to the previous mentioned articles, we mention here voltage control using VES [133] as one more example.

This survey shows that the literature for the topic of this research exists. Efforts are being made, but it is still widely undiscovered area with lots of space for new business models and enhancements in general. According to that, in scope of this use case, proposed models will bring further step forward and arguments to the discussion of how this approach may be utilized to generate profit/savings and reliability for all actors involved.

7.3 Basic system model to be followed

There are two main directions this research is heading for. The first one describes large FlexAsset owners willing to lease their storage capacity to several interested parties. This approach is on track of the ones mentioned in the chapter considering survey on the related works in international literature. Second direction is far more abstract, motivated with Airbnb, Booking.com, Uber and similar business models.

In the first approach, 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 (/lower costs), increase safety & reliability and postpone capital intensive actions using leased storage capacity that they do not own. Users may have various goals to achieve using energy storage systems, but when deciding whether to invest and buy their own storage system or to lease it, cost of acquiring their own storage system must be higher than paying a fee to the provider of storage assets having in mind expected lifetime of the respective storage system and similar factors. . Should the situation be contrary, there is no rational reason for a player not to acquire its own energy storage system as it is the cheaper solution. One of the assumptions is that the FlexAsset owner may acquire energy storage systems under lower prices due to the economies of scale and that it has various technologies that enable bigger flexibility when it comes to the specific demands of clients. So, not only that the potential user should benefit from lower prices, but he/she should benefit from even better (more diverse) energy storage characteristics (see Fig. 12), as at his own for a limited capacity one needs to choose specific technology (with respective technical characteristics). Prerequisite for viable business strategy is for FlexAsset owner to optimize:

- Amount of capacity to invest in (considering its own needs and possible lease demand) - sizing
- Location(s) of the energy storage systems - siting
- Technology mix in portfolio (different technologies, different characteristics)

* Prices

Of course, the FlexAsset owner may already have all required infrastructure (or at least some part of it), so capacity to invest depends also upon existing situation. Location may impact factors such as frequency of congestion occurrences and other relevant aspects that influence on the final size of revenue, while technology mix must be adequate to satisfy the needs of most lucrative services required in the observed network section. Finally, offered tariffs and packages must be attractive to the potential customers. On the other hand, end-user checks whether offered prices and declared characteristics of the energy storage suit his needs. Having in mind that FlexAsset owner offers its capacity (/power) to players who participate in various markets and need storage for various purposes (Fig.12), high-quality optimization may further enhance the business strategy, lower costs for the FlexAsset owner and, consequently, enable him to offer even more attractive prices that for individual player are far more acceptable than acquiring the same amount of capacity and type of technology on its own.

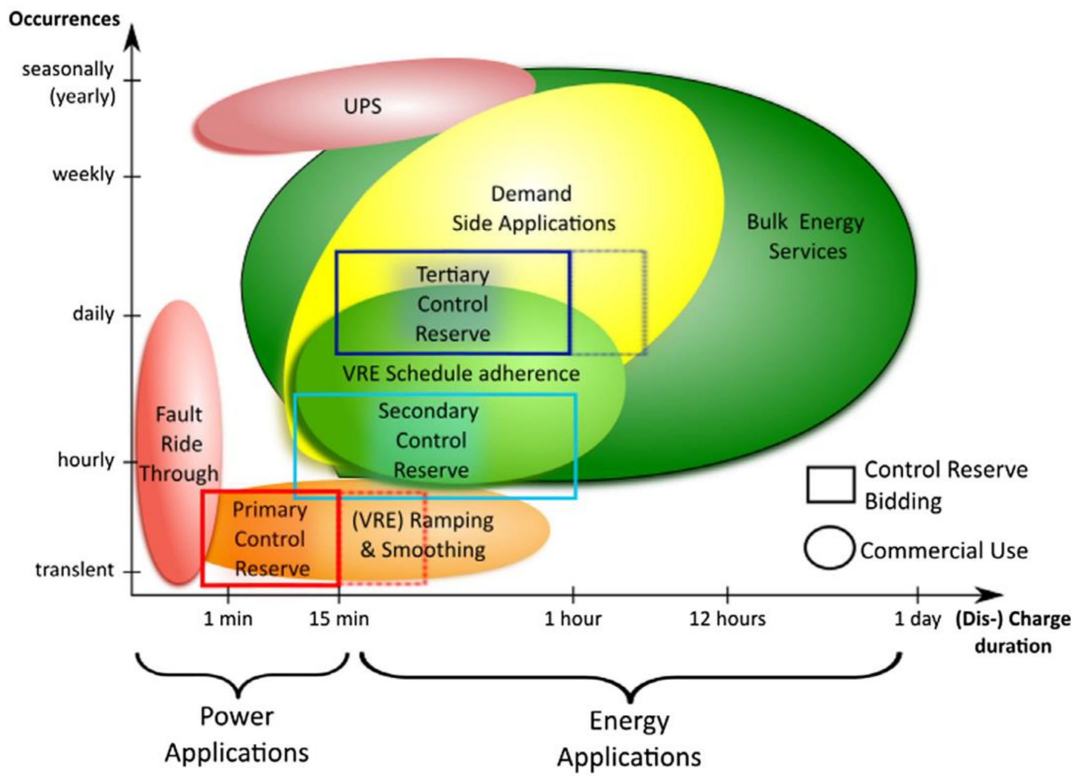

Figure 27: Average rate of occurrences and the typical charging/discharging duration [124]

The second approach is far more abstract. In this concept 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.

This kind of approach may bring multiple benefits, it should lower the entry barrier to the market (e.g. DA market) for smaller energy storage owners as their contribution adds up to the contribution of others almost erasing minimal capacity/power requirements for individual players. More precisely SMO enables small energy storage owner to participate in wholesale markets, which is currently not possible. Consequently, it incentivizes small (potential) prosumers and similar stakeholders to invest in storage systems as they may even generate income from it. On the other hand, it will presumably present attractive business model for the other side, users of the service offered on the platform. It may lower them overall costs, leaving the capital for other potential investments. 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.

Both mentioned approaches will be investigated, and concepts will be formulated. Moreover, comparison between the two of them and the current state will give some indications on what are the most promising strategies and whether they are feasible at all or not.

7.4 Basic problem formulation and algorithmic solutions

As stated in the previous subchapter, the case of leasing storage capacity to the interested parties is researched from two angles. Still, the emphasize is on the model where a large FlexAsset owner leases storage-. So, formulation and algorithmic solutions will be researched in a deeper manner than for the case where storage procurer and storage renter are connected using the service of platform run by an (independent) storage operator.

At the time of creating this deliverable, it is still not fully decided how to precisely approach towards modeling the interaction between large FlexAsset owner and interested parties. It is clear that the FlexAsset owner must optimize its portfolio in order to offer attractive packages to the bidders. Should the portfolio's cost be to high (both CAPEX and OPEX), there won't be any interest nor financially profitable strategy to begin with. Furthermore, characteristics of the FlexAssets must meet the needs of the potential end-users (activation time, capacity, power and even location). Assuming that the characteristics and prices of the offered FlexAssets services are attractive, potential users will then compete with each other for acquiring the services. In other words, the whole model will be presented as a bilevel problem. Upper level deals with the large FlexAsset owner investment problem, while the lower level problem considers the other players. Effort will be made to formulate the problem in such manner, so it is doable to relax it to single level problem using KKT conditions.

Regarding the second approach, it is based upon peer-to-peer business model where an entity (storage operator in our case) plays sort of a matchmaker between group of subjects that offer some service (storage in our case) and others willing to use that service. The operator provides the platform, regulations and procedures in general – from payment to bidding/offering instructions. Algorithmic solution will deal with price forming possibilities and matching the ones offering the service with others wanting it.

7.5 Datasets to be used for simulation setup and most important KPIs

To encompass all relevant aspects, needed dataset includes:

- Energy storage technical data
- Energy storage prices
- Distribution Network data (topology, lines' resistance/reactance and power capacities, voltage bounds)
- Hourly day-ahead energy market prices
- Hourly balancing market prices
- System's Upward/Downward reserve requirements by the TSO
- Hourly active power consumption of loads in the distribution network and their power factors

Proposed models' contributions to the involved stakeholders and system in general are manifold. From lower costs for users who procure the service, maximization of profit for the service providers to greater efficiency of the whole system and integration of RES.

Accordingly, following KPIs are relevant:

- Profit for the large FlexAsset owner
- Curtailment of RES
- Balancing costs
- Peak shaving (has the consumption curve flatten)
- Energy storage capacity in the system (significant increase)
- Congestion occurrence frequency
- Prosumers electrical bills (cost-profit)

8 FlexSupplier's Toolkit – FST

Chapters 2-7 explain the main points of research interest in the scope of WP4 under FLEXGRID project. FlexSupplier's Toolkit (FST) is the toolkit that integrates all of the submodules and functionalities needed to successfully run the models stated in the respective chapters. This chapter describes the operation of the mentioned toolkit and integration of the mentioned functionalities. Graphical user interface (GUI) structure, intended for ESP to use the toolkit in an easy to understand manner, shall also be described, but in a high-level abstraction.

Work done so far in FLEXGRID with respect to the FST is following:

- As part of the D2.1 [31], a requirements analysis has been conducted (both for FST S/W toolkit and the ESP user)
- As part of the D8.1 [134], an initial SWOT, business and market analysis has been undertaken for FST
- As part of the D2.2 [135], internal FST S/W architecture has been described including technical specifications and a draft data model to be followed concerning FST's algorithmic inputs/outputs

8.1 FST and ESP user requirement's analysis

The ESP user firstly needs to use his/her credentials to log in the FLEXGRID ATP, where the authentication process takes place. Having been authenticated, s/he is redirected to the FST GUI with associated access rights. All of the visualizations, simulation scenarios, parameters input and setup are frontend part of the whole software package. Meaning that all the functionalities that ESP user is able to user are a "black box" for him/her, so the user is able to change certain parameters, input some data, choose what of the available scenarios/simulations/algorithms wants to run and then get the results without exactly knowing what happened in the backend to produce those results. Short list of the FST's requirements follows:

- FST's intelligence will be an open-source S/W and modular-by-design in order to be easily integrated as a module of a more complex S/W platform such as FLEXGRID ATP.
- ESP should experience a user-friendly GUI as part of the FST, while backend system will accommodate all necessary functionalities and algorithms in scope of the WP4.
- FST should be able to: i) acquire ("pull") input data required for algorithms' execution, and ii) send ("push") algorithms' output data to the FLEXGRID database to be stored and retrievable when necessary. Thus, bi-directional API with the database will be used.
- FST should be able to: i) acquire ("pull") response related to the FlexRequest that FST must ii) send ("pull"). Thus, bi-directional API with the FLEXGRID ATP will be used.
- FST will allow multiple user categories and it will enable user profiling, searching and recommendation functionalities.
- FST will accommodate end-results' visualization, comparisons and export in general.

8.2 FST as an exploitable commercial asset

FST design makes this toolkit commercially exploitable as a standalone S/W toolkit with the possibility of integration in other suitable S/W platforms. Moreover, also in this project will FST toolkit be integrated in the larger S/W platform – FLEXGRID ATP. This platform hosts all of the functionalities and sub-platforms developed in the scope of FLEXGRID project. FST's functionalities will be tested trough laboratory experimentations and pilot tests organized under the WP7. The main target groups of FST are:

- Individual researchers and research groups, who want to use FST for research and experimentation purposes.
- Profit-oriented companies which may make contractual arrangements with various types of flexibility assets (here referred as ESPs and or RESPs).

8.3 FST S/W architecture, interaction with other subsystems and algorithms' integration

As graphically presented in the D2.2. [135], the internal FST S/W architecture comprises of the following S/W modules, which are to be developed within WP6:

- Web REST API for bi-directional data exchange between the central FLEXGRID database and the FST
- Web REST API for bi-directional data exchange between the core FLEXGRID ATP and the FST
- Data Acquisition module
- Forecasting Engine
- Optimal Bidding Algorithm Module
- Optimal Scheduling Algorithm Module
- FlexAsset Sizing/Siting Algorithm Module
- Task Execution/Monitoring Module
- Internal Database

According to the above presented list, two Web REST APIs are most relevant for the normal functioning of the FST. Regarding the first one, FST module initiates the communication with the central database when it requires inputs for operation of respective submodules, so the client-side REST API will be implemented at the FST side. On the other hand, one server-side REST API will be implemented at the central FLEXGRID database. When the server-side receives a request from the client-side (Data Acquisition Module), it prepares/retrieves the requested datasets from the central database and sends them back to the FST's Data Acquisition Module. Then Data Acquisition Module forwards the datasets to the appropriate module so the algorithm can run. Resulting output datasets are stored in FST's internal database.

When it comes to the ATP-FST communication, it is usually initiated by the ATP. Thus, the client-side REST API will be implemented at the core FLEXGRID ATP side, while the server-side will be implemented at the FST side. ATP's GUI will accommodate all of the FST-related needs for the visualization so the ESP user could easily access FST's functionalities that are run in backend. From simulation results, user profiling and parameter input to executing the desired algorithm by pressing a button. By starting the respective algorithm, the ATP REST client should automatically construct the declared datasets in a fine-grained JSON format and send them to the FST REST API server, which forwards these input datasets to the appropriate module depending on which algorithm needs to be executed. Output datasets are stored in FST's internal database, but they are available upon user's request to visualize them and/or further process them.

The "Forecasting Engine" developed by UCY module is used both in FST's and AFAT's toolkit portfolio. In the case of FST, the engine is used to help create strategies concerning ESP's business. The focus lies on the market prices and PV generation forecasting algorithms. Extensive technical details regarding the basic system model that is followed, basic algorithmic solutions to be adopted and KPIs to be measured are provided in chapter 2 of this deliverable.

The "Optimal Bidding Algorithm Module" is used to create optimal business strategies dependent on the ESP user preferences (e.g. CAPEX minimization, OPEX minimization…). The algorithm, according to the objective function (preferences) and given constraints, creates as the output optimal bidding strategy. Throughout chapters 3,4,5and 6 are listed different functionalities that the module needs to accommodate. From bidding to various markets (day-ahead, intraday, reserve markets…) in parallel, to respecting each FlexAsset constraints and regulations in general.

The "Optimal Scheduling Algorithm Module" is as vital to the FST as the previously described algorithm. Its task is to optimally schedule FlexAssets under the respective ESP's ownership in an optimal manner. From chapter three to the chapter seven, scheduling is important part of the algorithms in respective research problems. Scheduling algorithm in the cooperation with the bidding algorithm increases efficiency and utilization of the energy storage systems and reduces renewable energy curtailment to the lowest level feasible, having for consequence greater savings/profit.

The "FlexAsset Sizing/Siting Algorithm Module" is responsible for sizing and siting of FlexAssets in an optimal manner according to the ESP's input parameters and existing constraints. The emphasize on siting and sizing is especially given in the chapter four of this deliverable.

The "Task Execution/Monitoring Module" will be responsible for the execution and monitoring of the processing tasks (i.e. algorithmic runs) that have been submitted for execution in FST. This module will allow for submitting, canceling, and viewing the status of each submitted processing task by the aggregator user. It may also send notifications when there is a status update. Hence, the aggregator user will be able to easily monitor the progress of each processing task through its user-friendly GUI. Depending on the chosen time-horizon, quantity of input data and complexity of the algorithm itself, some tasks may present enormous computational burden and last for hours or even days. Thus, progress report is of the great assistance to the user waiting for the results.

Note: In chapter 7 of D2.2 [135] there is an extensive list of the required input and output data per algorithm category that will be created and exchanged among the above-mentioned S/W modules. The final version of the data models will be officially delivered in Month 18 through D6.1.

8.4 Draft structure of the ESP's Graphical User Interface (GUI)

This section provides a tentative list of web pages that the aggregator user will be able to visualize and use. As already stated in D2.2 [135], the WISECOOP S/W infrastructure developed by ETRA within the H2020 WISEGRID energy flagship project[7] will be used as a S/W substrate upon which additional novel FLEXGRID intelligence (cf. FST) will be integrated. In a nutshell, the ESP user will be able to visualize the following web pages:

- FST dashboard
- Executive page
- Results page
- FlexAssets page
- Network status page
- Market interaction page

The FST dashboard will be the first page that an ESP user sees when it logs in FST. It shall contain all the basic info and links to the functionalities that specific user has access to. Furthermore, it will contain basic information regarding FlexAsset, such as: i) State-of-Energy (SoE), ii) share of RES, iii) RES curtailment percentage, iii) topology of the network and locations of FlexAssets iv) OPEX v) NPV of CAPEX, vi) FlexAssets technical data vii) most important data for the last algorithm run.

The executive page is the most important page for a respective ESP user. It enables him/her choosing each of the developed algorithms in scope of FST with short description towards what each of them is oriented. When user choses appropriate strategy (from OPEX minimization to storage lease strategies), only relevant input parameters will pop-up, while other will be unavailable. User will be able for each of the functionality choose whether s/he wants to input own data or use some of the preexisting ones and run the simulations. After all of the parameters have been chosen and setup fully adjusted, user will be able to press "Execute" button. Algorithm will then execute, and results will be stored internally.

The results page will consist of visual and numerical results. The user will be able to choose from the list of available results what does s/he want to observe more carefully. Then the user will be able to zoom in/out the graph, move along the x-axis etc. Numerical results will be exportable, but also representative in form of user-friendly tables.

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

FlexAsset page enables the ESP user to fully monitor all relevant data for assets under its jurisdiction. Different technologies (BSSs, RES…) have different characteristics and different variables/parameters to monitor. According to the specific technology (which is part of ESP user's portfolio,), adequate data will be represented) From efficiency, utilization rate, markets where it operates on, state-of-health, state-of-energy, wind speed, Sun radiation, energy output…

For ESP that are also DSOs (or at least have access to DSO's information), the Network status page will present power flows, possible congestion locations and all other relevant network data.

Market interaction page will enable the ESP user to observe all the markets where s/he is eligible to compete on. It will contain the most important facts about specific markets (regulations, peculiarities…) then statistical data about trading of the ESP user on each of the markets (volumes, prices, profit…). This should present the ESP user really good overview what each of the markets brings to his/hers portfolio and how future market trends could look like (predictions according to chapter 2).

9 Conclusions

Conclusively, during the next months, FLEXGRID consortium will make further progress on the work described in this deliverable. This should result with S/W ready to be implemented as part of the FST to the FLEXGRID ATP. Meaning that the forthcoming work plan should look like as follows:

- According to this deliverable, basic system models alongside the problem formulation and algorithmic solutions were developed. Furthermore, necessary datasets have been listed, performance evaluation scenarios explained and KPIs mentioned
    - From the M13 onwards, partners are going to extend the basic models and start implementing algorithmic solutions. Having in mind the necessity to implement and integrate each of individual subsystems into the single modular-by-design FLEXGRID S/W platform.
- Next milestone is in the M18, alongside with the delivery of D4.2
    - The deliverable shall contain the description of the intermediate version of advanced ESP and RESP BMs
- The milestone in M26 concludes the whole project duration
    - Deliverable: Final version of the advanced ESP and RESP BMs

Please see Figure 28 for more illustrative example of the WP4's timeline as part of the FLEXGRID project.

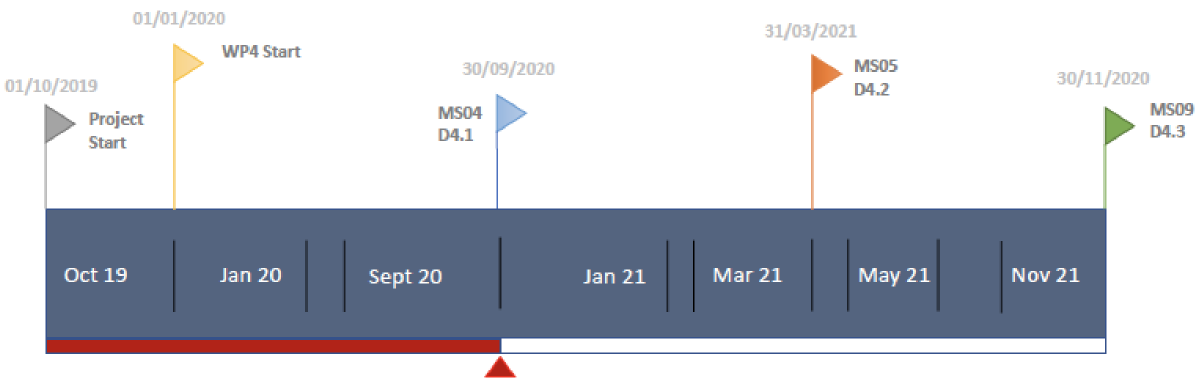

Figure 28: Current FLEXGRID project's WP4 timeline

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