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enabling new Demand REsponse Advanced, Market oriented and secure technologies, solutions and business models

DELIVERABLE: D3.3 Consumption flexibility models and aggregation techniques

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List of acronyms and abbreviations

API	Application Programming Interface
CHP	Combined Heat and Power
CSP	Constraint Satisfaction Problem
DEG	Distributed Energy Generators
DER	Distributed Energy Resources
DR	Demand Response
DSO	Distributed System Operator
eDREAM	enabling new Demand Response Advanced, Market oriented and secure technologies, solutions and business models
EES	Energy Storage Systems
EEX	European Energy Exchange
EPEX	European Power Exchange
ESS	Energy Storage System
FDA	Flexible Energy Demand Assets
GUI	Graphical User Interface
ILP	Integer Linear Programming
LV	Low Voltage
MILP	Mixed-Integer Linear Programming
MV	Medium Voltage
NLP	Nonlinear Programs
OOP	Object Oriented Programming
RES	Renewable Energy Sources
REST	Representational State Transfer
UPS	Uninterruptible Power Supply
VPP	Virtual Power Plant
WP	Work Package

Executive Summary

In this deliverable, we had provided models and techniques for enacting the dynamic construction of coalitions of prosumers in VPP such that different type of services may be provided in an optimal manner by the VPP.

We have started by analysing the existing literature approaches on VPP modelling and optimization identifying the main gaps that are to be filled by eDREAM: the lack in addressing different types of markets which usually translates in different optimization criteria multiple constraints and different time frames and the need for innovative optimization techniques which allow to address the complex optimization problems in a decentralized manner (Section 2).

Thus, we had proposed a new VPP model which allows the formalization of dynamic construction of coalitions of prosumers in VPPs as a constraint satisfaction problem which can be tailored and adapted to different types services to be offered (Section 3). The VPP model considers three types of prosumers distributed energy generators, energy storage systems and flexible energy demand assets and allow the specification for each individual case of local operational constraints that need to be fulfilled while providing services as part of a VPP. At the same time, it allows defining constraints that are specific to the type of services the VPP will provide as well as of customized optimization goal following to maximize the profit of the VPP coalition and service delivery. Specifically, we had formalized as constraint satisfaction problem the dynamic construction of VPPs to trade energy in the day ahead and intraday, sell on short notice (one hour ahead) replacement capacity to a power plant which can't meet its commitment, provide frequency regulation committing unused capacity and participate in direct demand response programs.

In Section 4 we propose a hybrid optimization technique which combines the gradient-based solutions with nature-inspired heuristics for achieving fully distributed platform for creation of prosumers coalition and targeting to implement it over blockchain based distributed computing platforms. The optimization approach first applies a heuristic to determine a valid solution for integer variables, then it sets the integer values as constants in the objective function making it differentiable and finally applies a gradient-based method by iteratively improving the value of variable considering the derivative of the objective function with respect to them.

Finally, Section 5 describes the design and technologies used to implement the eDREAM architectural component that deals with the dynamic coalitions of prosumers formation as well as the public REST API it exposes to other architectural components. Evaluation results are presented on different scenarios showing our approach feasibility in constructing coalitions for allowing VPP to meet specific levels of energy generation requests, optimal trading of energy and capacity bidding. The results show our hybrid optimization approach capability to improve the time overhead of solving the optimization problem at hand for many small prosumers the execution time increases linearly with the problem size.

1 Introduction

1.1 Purpose

This report provides an overview of the work carried out in the direction of defining models and optimization techniques aiming to create optimal coalitions of distributed energy prosumption sources targeting to provide services for DSO, participate in DR programs and participate as a whole in different types of markets such as the energy and capacity market. We have defined a generic VPP model of optimization technique on top which combines the gradient-based solutions with nature-inspired heuristics for achieving fully distributed platform for virtual generation of prosumers coalition and targeting to implement it over blockchain based distributed computing platforms.

The work has been done in relation with eDREAM project Task 3.3 “Multi-energy Distributed Generation Modelling and Virtual Power Plants” part of Work Package 3 “Techniques for DR and Energy Flexibility Assessment”.

1.2 Relation to other activities

WP3 uses the outputs of WP2 in terms of requirements and use-cases and implements the main models and techniques that will provide the underlying base for developing the eDREAM envisioned next generation of demand response services both in a classical, centralized approach (WP4) but also in innovative decentralized blockchain based manner in WP5 (Figure 1). In particular, the VPP model and decentralized optimization techniques will consider the outputs of the energy production / consumption forecasting tool developed in Task 3.1 and will may be implemented on top of the blockchain based platform developed in WP5 benefiting on the advantaged brought by this technology.

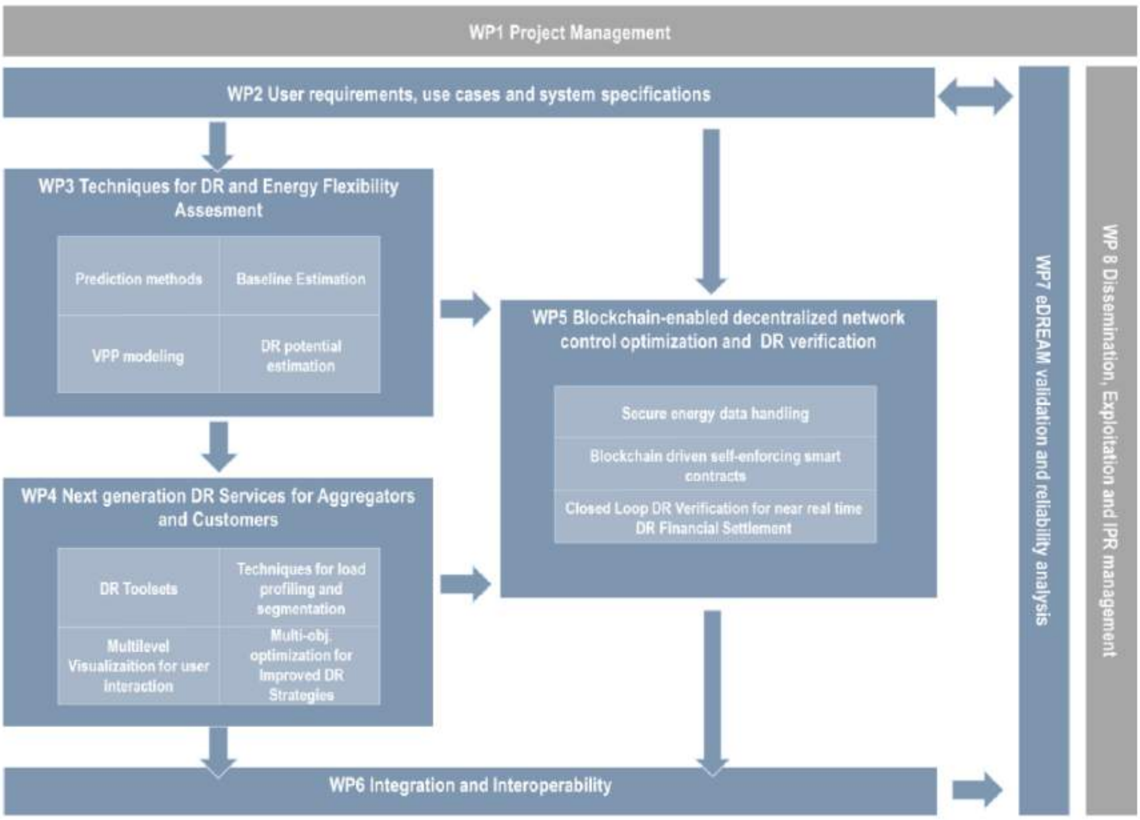

Figure 1. eDREAM pert diagram showing WP3 relations with other work packages

1.3 Structure of the document

The remainder of the report is organized as follows:

- Section 2 presents the most relevant literature approaches in the area of VPP modelling and optimization highlighting, in the end, the eDREAM progress beyond the identified state of the art;
- Section 3 describes the eDREAM model for VPP and the optimization problem formalization for different types of services the VPP may provide as CSPs
- Section 4 presents the gradient enhanced heuristic optimization solution which is used to solve the specific CSPs and have the potential to be decentralized and implemented on top of the blockchain platforms.
- Section 5 presents the architectures, main data models and public APIs the eDREAM component implementing the VPP construction and optimization solution as well as evaluation results;
- Section 6 concludes the deliverable and presents the future work to be addressed in next iterations.

2 Literature survey and eDREAM position

Traditionally, the energy grid is constructed around centralized broadcast-like mono-directional energy systems, where electricity is remotely generated by power plants and transported over complex energy networks and infrastructures to the consumption points, with significant costs for interconnecting remote areas.

Lately with the advent of intermittent decentralized renewable energy sources (RES) are completely changing the way in which the grids are managed to provide electricity to consumers, requiring advanced technology to preserve continuity and security of supply at affordable costs. Moreover, variations in energy production, either surplus or deficit, may threaten the security of supply, the lack of energy storage capabilities, leading to energy distribution systems overload and culminating with power outage or service disruptions.

To avoid these issues, the concept of Virtual Power Plants had emerged. A VPP [1] combines and coordinates different types of energy production sources with energy storage systems and assets featuring controllable loads to handle the stochastic nature of renewable energy production, energy price, etc. In literature, the VPP are classified into two categories commercial VPP and technical VPP [2]. The commercial VPP is basing on the characteristics and forecasts of energy production and consumption of all distributed energy resources from its portfolio to places bids/offers in different markets to create optimal day ahead operational schedules, etc. On the other hand, the technical VPP considers the near real-time the local network constraints on the aggregated profile of energy sources to provide ancillary services [3], [4].

Researching the state-of-the-art literature, there are papers that are concentrating on VPP creation and optimal interaction with the smart energy grid.

In [5] the VPP is optimally managed to minimize the operational cost considering the energy loss and energy price for the day ahead. The optimization problem is formalized as a constraint satisfaction problem which is solved using an Imperialist Competitive Algorithm under technical constraints. The proposed meta-heuristic optimization algorithm is used to determine optimal energy management of a VPP with renewable energy sources, such as wind turbine, photovoltaic, microturbine, fuel cell, energy storage and load control. In [4] the VPP day ahead and intraday optimal generation schedule is considered in relation with Demand Response programs. The stochastic parameters of the optimization problem are in this case forecasted wind energy production and energy price. The authors propose a profit based VPP scheduling model considering the Conditional Value-at-Risk [6] as a form of risk management in decision making which is effective in providing the needed feedback in relation with DR programs selection. The results are showing in described use-case over 30% improvement of VPP profit when participating in reserve and balance markets. A stochastic programming approach for optimal VPP participation in the day-ahead energy market and near real-time balancing market is proposed in [7]. The authors consider the uncertainty in energy price, generation and consumption of energy and model them as a form of conditional value-at-risk when placing bids and offers which will eventually affect the VPP profit. The VPP consider the renewable energy generation forecasted values from making day ahead energy bids/offers and if the generation surplus/consumption deficits are registered they are traded in the near real time market. The authors propose the use of cooperative game theory approaches to split and allocate VPP’s profit to the aggregated distributed energy resources. The authors of [8] investigate various trading strategies of a VPP in cooperation with neighbouring VPPs in respect to the wholesale electricity markets. Two risk management strategies are used to deal with market price uncertainty and its impact on profit variability: conditional value at risk and second-order stochastic dominance constraints. The optimization problem is modelled as a mixed-integer linear programming and used to assist VPP managers in making medium-term energy trading. The results show that the second-order stochastic dominance constraints approach allow the VPP manager to impose his preferences on the resulting profit, while the conditional value at risk makes the optimization problem computationally more tractable and solvable in a reasonable time. A probabilistic model for optimal day ahead scheduling of electrical and thermal energy resources in a VPP in defined in [9] considering the participation energy and spinning reserve markets. The VPP's scheduling problem considers the uncertainties in relation to the market price, energy demand and generation which are modelled using the Point Estimate Method. The results show that the VPP can compensate a plausible shortage of committed energy to the energy market due to existing uncertainties and may bid the specific amounts of reserve to the spinning reserve market. This could increase VPP's profit and reduce its dependency on the upstream network. In [10] the problem of trading of VPP aggregated energy in day-ahead and the balancing markets to maximize the expected profit is modelled as a two-stage stochastic mixed-integer linear programming model. The uncertainty in renewable energy generation and energy price are modelled via scenarios based upon historical data. The results show that the proposed model can maximize the VPP short term profit while most of the energy trading decisions take place in the day-ahead market, while the balancing market makes less than 2% of the revenue. The model can be extended to consider the possibility that the VPP producer is able to influence market prices by upgrading the stochastic programming method by explicitly consider the market clearing process as in [11]. In a similar manner, the energy aggregators opportunities to manipulate the energy price in electricity markets is discussed in detail in [12]. The authors study the problem of estimating the profit an aggregator may obtain through and show that even if it is computational hard efficient algorithms exist when the topology of the network is acyclic. In [13] the authors analyse the aggregation of stochastic and deterministic Renewable Energy Sources in a VPP to reliable generate energy which can be traded in the European Power Exchange (EPEX)/European Energy Exchange (EEX) using existing market products. The optimal economic VPP configuration is analysed in correlation with the standard power market products highlighting the dependence on energy availability and the marginal costs of the VPP aggregated distributed energy sources.

The VPP construction model is analysed in detail in [14] and the decision area variables are determined with the goal of establishing a unified and coordinated control of the distributed energy resources. Regional load density, power consumption levels, administrative ranks, economic levels and user importance are considered as criteria for determining the VPP decision area. The authors propose the use of the improved bat algorithm based on priority selection to obtain the construction scheme of VPP, which satisfies the multi-objective programming criteria defined. The proposed solution does not consider the uncertainty of some distributed energy resources output. A novel VPP architecture which aim at aggregating distributed energy resources with the physical domain limited to single Points of Delivery of the distribution network is introduced in [15]. The optimization solution is based on agents representing individual energy resources which cooperate to implement the optimal management of the prosumer's assets considering price and event-based DR schemes. The advantage brought by this approach is the level of decentralization the control being moved in the energy resources side. The optimization problem is modelled as a Mixed-Integer Linear Programming (MILP) problem aiming to solve the defined scheduling and DR constraints while minimizing the operational costs. In [16] critical review of literature approaches in relation to VPP and multi-energy systems and relationship among them is conducted. The authors advocate the potential role of agents and semantics in managing such distributed energy components. They propose the adoption of holonic energy systems as a new management paradigm targeting efficient decentralization through adaptive control topologies and demand responsive energy management while adding features such as local autonomy and global energy balance. The authors of [17][identify VPP as a key instrument for distributed energy resources integration and propose an algorithm to optimize the day-ahead thermal and electrical scheduling of a large scale VPP. The algorithm can provide support in the implementation of strategies for the VPP daily profit maximization in the presence of hourly prices of fuel and electricity. The authors clearly identify the need of decision support system for the VPP coordinators which need to consider huge amounts of data such as individual resource power production / consumption, size, efficiency, typology and remuneration. [18] consider VPP coalitions of wind generators and electric vehicles where the vehicles are modelled using software agents and used as energy storage devices. The remuneration for storage is provided as charging entitlements allowing the electric vehicles to take advantage of the energy price in the wholesale and retail. The authors propose a VPP operational optimization model based on linear programming allowing the VPP to increase its profit while paying the electrical vehicles.

The authors of [19] had defined the arbitrage strategy for VPPs by participating in energy market and ancillary services market targeting the spinning reserve and reactive power services. The optimization model considers the supply–demand balancing, transmission network topology and security targeting the VPP's profit maximization. The model is translated into a mixed-integer non-linear optimisation problem with inter-temporal constraints, the result being a single optimal bidding profile and a schedule for managing active and reactive power under participating in the markets. In [20] a two-stage stochastic programming approach is used to address the problem of VPP trading in a market of energy and ancillary services. It incorporates a risk-averse optimal offering model based on conditional value-at-risk while considering the uncertainty about energy generation/consumption and energy prices in spinning reserve and balancing market.

[21] address the problem of optimal coalition of heterogeneous distributed energy resources by a virtual power plant considering weekly bilateral contracting, futures-market involvement, and pool participation. The output is an optimal portfolio of available energy resources to provide a certain service. The selection is done in two stages: in the first stage based on long term considering futures-markets and bilateral contracts and in the second stage based on the most plausible realizations of the stochastic prices in the day-ahead market. In [22] a methodology for creating coalitions of distributed generation units based on game theory is proposed. It features a classification model of distributed energy resources considering fourteen parameters including technical, economic and behavioural ones. VPPs constructed in this way can participate in demand response programs at the level MV and LV distribution network. An optimal coalition formation mechanism of distributed energy sources using game theoretical perspective is described in [23]. A hierarchical coalition formation is proposed to achieve a state of cooperative equilibrium among the distributed energy sources while providing the best possible response to the DSO requests. The authors show that their proposed scheme provides optimal outcomes and it is scalable enough to participate in real-time operation.

Analysing the state of the art is can be seen that there are few approaches addressing the problem of dynamic construction of coalitions of energy resources to provide an aggregated energy generation for trading or for providing services for other players such as the DSO (see the spider web chart from Figure 2). At the same time, only few approaches consider in the VPP optimization problem from the perspective of different types of markets which usually translates in different optimization criteria multiple constraints and different time frames. eDREAM progress the state of the art by providing and generic VPP optimization model which allows the definition, formalization and provisioning of different types of energy or ancillary services. Also, there are state of the art approaches which address jointly the problem of uncertainty in energy generation and consumption and VPP optimization but only from a centralized perspective using stochastic programming approaches. eDREAM will provide on top of the model an optimization technique which innovatively combines gradient-based solution with nature-inspired heuristics having the potential to address the VPP optimization problem in a des centralized manner which may be implemented over the blockchain. When it comes to decentralization there is no state-of-the-art approach to model the optimization problems in a decentralized fashion up to the level of individual energy resources.

Figure 2. VPP analysis of the state of the art and eDREAM positioning

3 VPP model and optimization problem formalization

Our aim is to provide the underlying model to create dynamic coalitions, which aggregate distributed energy prosumers of various types in VPPs:

- Distributed Energy Generators (DEG) such as small-scale wind power plants, photovoltaic units, CHP systems, diesel generators, etc.
- Energy Storage Systems (EES), such as batteries, UPS
- Flexible Energy Demand Assets (FDA).

The goal is to manage them optimally to address the variable generation and uncertainty at the micro-grid level by providing different type of services to the DSO while optimizing the profit of VPP participants (See Figure 3).

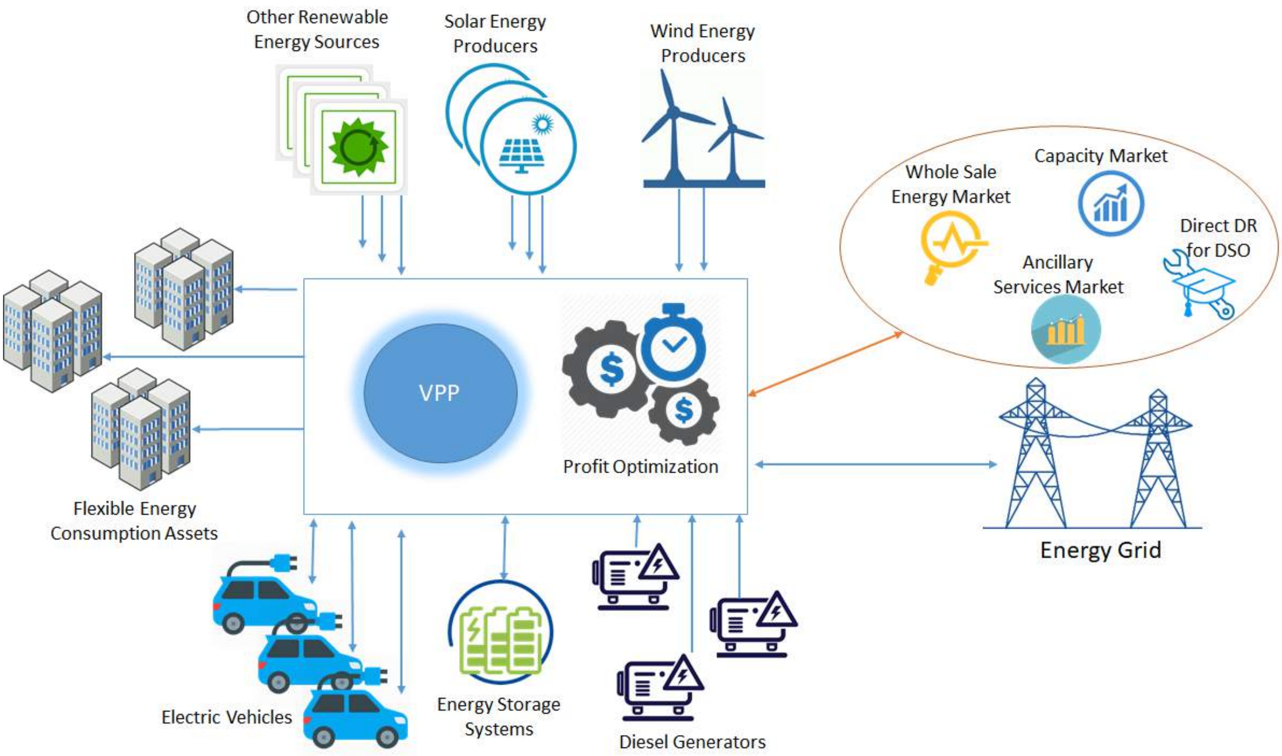

Figure 3. VPP model considered

We have considered that the VPP may operate in different type of markets, such as the wholesale electricity market, balancing market and the ancillary services market targeting the delivery of different types of services (see Table 1):

In the wholesale **electricity market,** a VPP may buy energy when the prices are low and charge energy storage systems. When the prices are high the VPP will sell the energy surplus and at the same time can adjust the demand of controllable, flexible assets and discharge power from the energy storage systems. In this sense, it will act an intermediary between the DER and energy market allowing the participation of small scale DER that are not qualified to participate on their own.

In the **balancing market,** the VPP can sell on short notice (one hour ahead) replacement capacity to a power plant which can't meet its commitment. Also, it may offer to either increase or decrease generation (or consumption) during a certain time period.

In the **ancillary services market** may provide short term services such as frequency regulation committing unused capacity such as the diesel generators.

Table 1. VPP optimization targeted services

Service Name	Description	Market Type	Time
Trade Energy	VPP is created to sell extra energy production on the market when the prices are high or to buy energy when the prices are low and store it in ESS.	Energy Market	Day Ahead or Intraday
Capacity Bidding / Selling	In case a power plant cannot meet its commitment and needs to purchase replacement capacity a dynamically created VPP may offer it.	Balancing Market	One Hour Ahead
Reactive power compensation	Frequency regulation. Unused capacity which can be activated to modify the reactive power. DEGs of specific type can be used to offer frequency balancing by injecting inductive reactive power in the grid.	Ancillary Services	Near Real Time
VPP demand response	Group energy prosumers to offer a demanded energy supply amount over a time window also considering the potential flexibility of FDAs.	Direct for the DSO / fixed remuneration	

We model a distributed energy prosumer as a triple consisting of the predicted energy profiles over a future time interval T in which the VPP is constructed, and the prosumer type (DEG, EES, FDA):

$$Prosumer[k] = (E_K[T], \{DEG, EES, FDA\})$$

The energy profile of the prosumer is represented as a set of energy values sampled at equidistant time stamps during the time interval T over which the VPP coalition will provide a specific service.

$$E_k(T) = \{E_K(i) | i \in \{0..T\}, k \in \{1..N\}\}$$

We consider that in the local grid there are a number N of distributed energy prosumers of different types and scales (energy profiles) each having their specific local constraints which need the be met.

$$N = C + P + S$$

where C is the number of flexible energy assets, P is the number of energy producers and S is the number of energy storage devices.

The goal of the optimal coalition of prosumers construction process is to select a subset of the energy prosumers from local grid available portfolio which fulfils best the optimization objectives defined for the type of energy service that is targeted to be delivered by the VPP, while meeting each energy prosumer local constraints.

We represent the generated coalition as a binary array of length N, where 0 value on position k means that prosumer k is not part of the coalition while 1 means that the prosumer is taken into the coalition.

$$VPP = \{(taken_k, Prosumer[k]) | k \in \{1..N\}, taken_k \in \{0,1\}\}$$

$$taken_k = \begin{cases} 0, Prosumer[k]\ is\ not\ part\ of\ the\ VPP \\ 1, Prosumer[k]\ is\ part\ of\ the\ VPP \end{cases}$$

The search space of the optimization problem is 2^N, the set of all subsets that can be formed with elements of a set of cardinality N, making the search problem NP-complete. Thus, we define the VPP coalition formation for specific services as a CSP which will be solved using the gradient enhanced heuristic optimization solution defined in Section 4.

For the **Distributed Energy Generators**, we consider the following parameters and local constraints in operation:

- E_K – the forecasted energy generation values;
- U_L and U_H – the lower and upper levels of uncertainty considered in the forecasting process;
- $E_{MAX}^{generation}$ – the maximum energy generation;

The lower and upper limit of uncertainty give the lower and upper bounds of the energy predictions considering potential prediction errors reported to the actual value that will be monitored in the future:

$$U_L * E_K(i) \leq E_K^{uncerntainty}(i) \leq U_H * E_K(i) \leq \ E_{MAX}^{generation}, \forall i \ \in \{0..T\}$$

The total energy generated by the producers selected in a VPP can be computed as the sum of each individual prosumer energy generation:

$$E_{VPP}^{generation}(t) = \sum_{k=1}^{P} taken(k) * E_K^{uncerntainty}(t)$$

Furthermore, the coalition is created considering the risk management in the optimization decision making generated by the uncertainty in the energy generation forecasting processes. This is computed as the weighted difference (ρ) between the forecasted value of the prosumer energy profile E_K and the actual values during delivery and represents a cost in optimization problem. When the difference is high, the probability of not meeting the forecasted energy values increases, thus increasing the risk of not being able to supply the energy desired directly impacting the value of profit estimated:

$$risk_{uncertainity} = \rho * \sum_{k=1}^{N} \sum_{t=1}^{T} |E_K^{uncerntainty}(t) - E_K(t)|$$

For the **Energy Storage Sources,** the following parameters and local constraints in operation have been considered:

- Maximum capacity: $MAX_K^{Load}[kWh], k \in \{1..S\}$
- Depth of Discharge: $DoD_k, k \in \{1..S\}$
- Initial state: $ESS_k^{init}[kWh]\ , k \in \{1..S\}$
- Maximum Charge Rate on time interval: $MAX_K^{Charge}[kWh], k \in \{1..S\}$
- Maximum Discharge Rate on time interval: $MAX_K^{Discharge}[kWh], k \in \{1..S\}$
- Actual Charging Rate on a time interval: $C_{ESS}^k[kWh], k \in \{1..S\}$
- Actual Discharging Rate on a time interval: $D_{ESS}^k[kWh], k \in \{1..S\}$
- Actual Loaded Capacity: $ESS_k[kWh], k \in \{1..S\}$
- Charge loss factor: $\varphi_C \in [0,1]$
- Discharge loss factor: $\varphi_D \in [0,1]$

- Discharge Cost per unit: $COST_k^D[\frac{€}{[kWh]}]$, $k \in \{1..S\}$
- Charge Cost per unit: $COST_k^C[\frac{€}{[kWh]}]$, $k \in \{1..S\}$

The constraints resulting from these parameters state the battery actual loaded capacity must be bounded by the maximum capacity and by the depth of discharge (DoD_K). Furthermore, the charge and discharges also must be bounded.

$$DoD_K * MAX_K^{Load} \leq ESS_k(t) \leq MAX_K^{Load} \; k \in \{1..S\}, t \in \{1..T\}$$

$$0 \leq C_{ESS}(t) \leq MAX_K^{Charge}, k \in \{1..S\}, t \in \{1..T\}$$

$$0 \leq D_{ESS}(t) \leq MAX_K^{Discharge}, k \in \{1..S\}, t \in \{1..T\}$$

$$ESS_k(0) = ESS_K^{init}, \forall k \in \{1..S\}, t \in \{1..T\}$$

When the battery is discharged over a time interval with D_{ESS}^k kWh, its actual loaded capacity decreases with $(\varphi_D + 1) * D_{ESS}^k$, due to the discharge losses. Furthermore, when a battery is charged, the actual loaded capacity increases with $(1 - \varphi_C) * C_{ESS}^k$, due to the charging losses. A battery cannot be charged and discharged simultaneously.

$$ESS_k(t) = ESS_k(t-1) + (1 - \varphi_C) * C_{ESS}^k(t) - (\varphi_D + 1) * D_{ESS}^k(t), k \in \{1..S\}, t \in \{1..T\}$$

$$C_{ESS}^k(t) * D_{ESS}^k(t) = 0, k \in \{1..S\}, t \in \{1..T\}$$

We consider that the charge and discharge of a battery are increasing its operating costs due to wear and decrease the overall VPP profit. The operating cost of the battery over a time interval $[0..T]$ is computed as the negative cost due to battery charge and discharge:

$$OP_{cost}\left(C_{ESS}^k, D_{ESS}^k, price\right) = \sum_{t=1}^{T}((1 - \varphi_C) * C_{ESS}^k(t) * COST_k^C + (\varphi_D + 1) * D_{ESS}^k(t) * COST_k^D))$$

The overall energy charged and discharged by the batteries over a time interval can be computed as the sum of the energy charged or discharged by each individual battery from the grid:

$$C_{ESS}(t) = \sum_{k=1}^{S} C_{ESS}^k(t); \quad D_{ESS}(t) = \sum_{k=1}^{S} D_{ESS}^k(t)$$

The overall cost of charging and discharging the batteries over the optimization interval $[0..T]$ is computed as the sum of the costs for each battery usage.

$$OP_{cost}(C_{ESS}, D_{ESS}, price) = \sum_{k=1}^{S} OP_{cost}\left(C_{ESS}^k, D_{ESS}^k, price\right)$$

The reward of operating the batteries selected in a VPP by selling and buying energy from the energy marketplace considering the energy price is defined as:

$$R_{ESS}(C_{ESS}, D_{ESS}, price) = \left(\sum_{t=1}^{T}\left(D_{ESS}(t) - C_{ESS}(t)\right) * price(t)\right) - OP_{cost}(C_{ESS}, D_{ESS}, price)$$

For the **Flexible Energy Demand Assets**, the following parameters and local constraints in operation have been considered:

- $E_K^{baseline}$ – the baseline energy consumption of the flexible asset;
- $APC_{Below}^{flexibility}$ – the lower bound of average energy consumption defined as the values of the actual energy measured that are below the baseline;

- $APC_{Above}^{flexibility}$ – the upper bound of the average energy consumption defined as the actual energy measured that are below the baseline;
- $E_{MAX}^{flexibility}$ – the maximum energy consumption of the flexible asset

The constraints defined for the flexible assets state that each one of them may provide a certain amount of flexibility either for increasing or decreasing their energy profile which is bounded by their adaptability power curve parameters (above or below):

$$0 \leq APC_{below}^{flexible} \leq E_K^{uncerntainty}(t) \leq APC_{above}^{flexible} \leq E_{MAX}^{flexibility}$$

The total energy flexibility that can be potentially elicitated by the selected prosumers in a VPP is defined as the sum of the energy profiles of the selected prosumers.

$$E_{VPP}^{flexibility}(t) = \sum_{k=1}^{C} taken(k) * E_K^{uncerntainty}$$

Each different generation type exposes the coalition to various risks due to weather conditions, thus diversity of generation being an important feature of the coalition. Thus, we define a risk measure to increase the diversity of the types of the prosumers selected in a coalition. We consider the total number of different prosumer types as VPP_{Types}, while the number of selected prosumers in a solution is denoted as $VPP_{size} = \sum_{k=1}^{N} taken_k$. If each prosumer would be evenly distributed, it should be $\frac{VPP_{size}}{VPP_{Types}}$ from each different type. So, we define the diversity measure as the Euclidean distance between the number for each selected different prosumers' type and the mean $\frac{VPP_{size}}{VPP_{Types}}$.

$$risk_{diversity} = \sigma * \sqrt{\sum_{p=1}^{VPP_{Types}} (\frac{VPP_{size}}{VPP_{Types}} - \sum_{k=1}^{N} taken(k) * (Prosumer_K.type == p))^2}$$

3.1 VPP energy trading

In this case the goal is to create an optimal coalition of prosumers to be able to trade aggregated energy generation and considering the energy price signals (i.e. to sell energy when the price is high or to buy energy when the price is low and store it in batteries).

We had formalized the optimization problem as a CSP (see Figure 4), having as inputs the set of energy prosumers available to participate in the VPP (i.e. available portfolio), the minimum bound of the energy traded on the market ($\mathrm{Min}_{\mathrm{trade}}$) and the energy price $Price[T]$ over the time interval T in which the coalition will be constructed.

The output of the optimization problem will be the subset of prosumers that optimal met the optimization objective while also fulfilling their individual operational constraints defined in above.

The profit obtained by trading the energy on the marketplace considering the energy price for each hour is computed as a sum between the revenue of the trading process and the revenue in operating the batteries while subtracting the cost associated with energy generation, forecasting process uncertainty and generation type diversity:

$$VPP_{profit}^{trading}(t) = \sum_{t=1}^{T} E_{VPP}^{generation}(t) * price(t) + R_{ESS}(C_{ESS}, D_{ESS}, price)$$
$$-(risk_{uncertainity} + risk_{diversity} + Gen_{Cost})$$

The objective function defined aims to maximize the profit obtained by the coalition, by choosing the best prosumers to participate:

$$\max VPP_{profit}^{trading}$$

Inputs: $Prosumer[N], Price[T], \mathrm{Min}_{\mathrm{trade}}$

Outputs: VPP – *subset of prosumers which met the defined objective*

Determine

$VPP = \{(taken_k Prosumer[k]) | k \in \{1..N\}, taken_k \in \{0,1\}\}$

Such that

$\max VPP_{profit}^{trading}$

Considering the constraints expressed as equalities:

C1: $E_{traded}(t) = E_{VPP}(t) - C_{ESS}(t) + D_{ESS}(t)$

C2: $C_{ESS}(t) = \sum_{k=1}^{S} C_{ESS}^{k}(t)$

C3: $D_{ESS}(t) = \sum_{k=1}^{S} D_{ESS}^{k}(t)$

C4: $E_{VPP}(t) = \sum_{k=1}^{N} taken_k * E_K^{uncerntainty}(t), \forall t \in \{1..T\}$

C5: $risk_{uncertainity} = \rho * \sum_{k=1}^{N} \sum_{t=1}^{T} |E_K^{uncerntainty} - E_K(t)|, \forall t \in \{1..T\}, k \in \{1..N\}$

C6: $VPP_{size} = \sum_{k=1}^{N} taken_k$

C7: $risk_{diversity} = \sigma * \sqrt{\sum_{p=1}^{VPP_{Types}} \left(\frac{VPP_{size}}{VPP_{Types}} - \sum_{k=1}^{N} taken(k) * (Prosumer_K.type == p)\right)^2}$

C8: $C_{ESS}^{k}(t) * D_{ESS}^{k}(t) = 0$

C9: $ESS_k(t) = ESS_k(t-1) + (1 - \varphi_C) * C_{ESS}^{k}(t) - (\varphi_D + 1) * D_{ESS}^{k}(t)$

C10: $OP_{cost}(C_{ESS}^{k}, D_{ESS}^{k}, price) = \sum_{t=1}^{T}((1 - \varphi_C) * C_{ESS}^{k}(t) * COST_K^C + (\varphi_D + 1) * D_{ESS}^{k}(t) * COST_K^D))$

C11: $OP_{cost}(C_{ESS}, D_{ESS}, price) = \sum_{k=1}^{S} OP_{cost}(C_{ESS}^{k}, D_{ESS}^{k}, price)$

C12: $R_{ESS}(C_{ESS}, D_{ESS}, price) = \left(\sum_{t=1}^{T}\left(D_{ESS}(t) - C_{ESS}(t)\right) * price(t)\right) - OP_{cost}(C_{ESS}, D_{ESS}, price)$

Considering the constraints expressed as inequalities (variable bounds):

C13: $DoD_K * MAX_K^{Load} \leq ESS_k(t) \leq MAX_K^{Load}\ k \in \{1..S\}, t \in \{1..T\}$

C14: $0 \leq C_{ESS}(t) \leq MAX_K^{Charge}, k \in \{1..S\}, t \in \{1..T\}$

C15: $0 \leq D_{ESS}(t) \leq MAX_K^{Discharge}, k \in \{1..S\}, t \in \{1..T\}$

C16: $ESS_k(0) = ESS_K^{init}, \forall k \in \{1..S\}, t \in \{1..T\}$

C17: $E_{traded}(t) \geq Min_{trade}, t \in \{1..T\}$

C18: $U_L * E_K(i) \leq E_K^{uncerntainty}(i) \leq U_H * E_K(i) \leq E_{MAX}^{generation}$

Figure 4. Optimal VPP construction for trading energy modelled as CSP

3.2 Capacity bidding service

The capacity bidding service aims at determining the optimal set of prosumers that create a coalition able to deliver a fixed energy $capacity\ [MWh]$ over the time interval $[0..T]$. The inputs of the optimziation problem defined in Figure 5 are the predicted energy profiles of the prosumers within the local grid, the capacity needed to be delivered and the associated compensation, while the output of the optimization problem is the VPP coalition created.

The optimization problem objective is twofold and aims to aggregate the target capacity from available prosumers while maximizing the VPP profit:

$$min(\sqrt{\sum_{t=1}^{T}\left(E_{VPP}(t) - Target_{capacity}\right)^2})$$

$$\max VPP_{profit}^{capacity} = Compensation * \sum_{t=1}^{T} E_{VPP}(t)$$

$$-(risk_{uncertainity} + risk_{diversity} + Gen_{Cost})$$

$\boldsymbol{Inputs}: Prosumer[N], capacity$ $\boldsymbol{Outputs}: VPP - subset\ of\ prosumers\ which\ met\ the\ defined\ objective$ **Determine** $VPP = \{taken_k \mid k \in \{1..N\}, taken_k \in \{0,1\}\}$ **Such that** $min((\sqrt{\sum_{t=1}^{T}\left(E_{VPP}(t) - Target_{capacity}\right)^2})$ and $\max VPP_{profit}^{capacity}$ **Considering the constraints expressed as equalities:**   C1: $E_{VPP}(t) = \sum_{k=1}^{N} taken_k * E_K^{uncerntainty}(t), \forall t \in \{1..T\}$ C2: $risk_{uncertainity} = \sum_{k=1}^{N}\sum_{t=1}^{T} \lvert E_K^{uncerntainty}(t) - E_K(t)\rvert, \forall t \in \{1..T\}, k \in \{1..N\}$ C3: $VPP_{size} = \sum_{k=1}^{N} taken_k$ C4: $risk_{diversity} = \sqrt{\sum_{p=1}^{VPP_{Types}}(\frac{VPP_{size}}{VPP_{Types}} - \sum_{k=1}^{N} taken_K * (Prosumer_K.type == p))^2}$ **Considering the constraints expressed as inequalities (variable bounds):**   C5: $U_L * E_K(i) \leq E_K^{uncerntainty}(i) \leq U_H * E_K(i) \leq E_{MAX}^{generation}$

Figure 5. Optimal VPP construction for capacity bidding modelled as CSP

3.3 VPP demand response

In this case of participation in demand response programs the DSO sends a demanded energy profile that has to be followed by the coalition formed by the VPP over a future time interval T and the associated reward

$$< \{E_{demand}(t) \mid t \in T, Reward >$$

The optimization problem (see **Error! Reference source not found.**) defined aims at selecting a subset of the e nergy prosumers that grouped together form a coalition able to fulfil the DSO demand while minimizing the risk due to the uncertainty of the predictions and also involving a diversity of type of energy generated (wind, photovoltaic, geothermal, etc.). Furthermore, because the coalition is also based on flexible assets, that can modify their demand either by increasing or decreasing it the overall reward must exceed the potential costs due to flexibility adaptation (e.g. use energy generation to compensate an increased energy demand in the local grid).

$$\min \sqrt{\sum_{t=1}^{T} \left((E_{VPP}^{generation}(t) + E_{VPP}^{flexibility}) - DSO_{Demand}(t) \right)^2}$$

$$\max VPP_{profit}^{DR} = \left(\left(\sum_{k=1}^{N} \sum_{t=1}^{T} \left| E_{uncertain}^{k}(t) - E_{K}^{baseline}(t) \right| * price(t) \right) - DSO_{Reward} \right) - (risk_{uncertainity} + risk_{diversity} + Gen_{Cost})$$

Inputs: $Prosumer[N], E_{demand}(t), Reward, T$

Outputs: $VPP -$ $subset\ of\ prosumers\ which\ met\ the\ defined\ objective$

Determine

$VPP = \{(taken_k Prosumer[k]) | k \in \{1..N\}, taken_k \in \{0,1\}\}$

Such that

$\min(\sqrt{\sum_{t=1}^{T} \left((E_{VPP}^{generation}(t) + E_{VPP}^{flexibility}) - DSO_{Demand}(t) \right)^2}$ and $\max VPP_{profit}^{DR}$

Considering the constraints expressed as equalities:

C1: $E_{VPP}^{generation}(t) = \sum_{k=1}^{P} taken(k) * E_{K}^{uncerntainty}(t), \forall t \in \{1..T\}$

C2: $E_{VPP}^{flexibility}(t) = \sum_{k=1}^{C} taken(k) * E_{K}^{uncerntainty}, \forall t \in \{1..T\}$

C3: $risk_{uncertainity} = \sum_{k=1}^{N} \sum_{t=1}^{T} |E_{K}^{uncerntainty}(t) - E_{K}(t)|, \forall t \in \{1..T\}, k \in \{1..N\}$

C4: $VPP_{size} = \sum_{k=1}^{N} taken_k$

C5: $risk_{diversity} = \sqrt{\sum_{p=1}^{VPP_{Types}} \left(\frac{VPP_{size}}{VPP_{Types}} - \sum_{k=1}^{N} taken_K * (Prosumer_K.type == p) \right)^2}$

Considering the constraints expressed as inequalities (variable bounds):

C6: $U_L * E_K(i) \leq E_{K}^{uncerntainty}(i) \leq U_H * E_K(i) \leq E_{MAX}^{generation}$

C7: $0 \leq APC_{below}^{flexible} \leq E_{K}^{uncerntainty}(t) \leq APC_{above}^{flexible} \leq E_{MAX}^{flexibility}$

Figure 6. DR service optimization problem

3.4 Reactive power compensation service

We propose the dynamic creation of prosumer coalitions around a point in the local grid where an imbalance of reactive power is identified such that the new VPP can address in an optimal manner the reactive power fluctuation locally and stabilize the grid voltage.

To create this kind of coalitions we have extended the prosumer model to incorporate both active and reactive power components which are correlated though the prosumer power factor PF. The power factor is defined as the ratio between the active and apparent power, and it is a value between 0 and 1. The closer to 1 the power factor is, the circuit has less reactive power.

$$Prosumer[k] = (E_{K}^{active}[T], E_{K}^{reactive}[T], PF_{TYPE}, \{DEG, EES, FDA\})$$

The loads in the Smart Grid can have either a lagging power factor, or a leading power factor:

$$PF^{TYPE} = \{lagging, leading\}$$

A load that “supplies” reactive power is a capacitive load with a leading power factor, while a load that “consumes” reactive power is an inductive load with a lagging power factor. A leading power factor implies that the reactive component of the power, is negative because reactive power is supplied to the circuit and the phase angle in this case is in the fourth quadrant. Furthermore, a lagging power factor means that the reactive component of the power, is positive because reactive power is consumed from the circuit, and the phase angle in this case is in the first quadrant.

Furthermore, if the resource has a constant power factor, then the bounds are given as equal. Using the general active and reactive power formulas as well as the power factor type (leading or lagging) of a resource, the active –reactive energy relationship is the following:

$$E_K^{reactive}(t) = \begin{cases} -E_K^{active}(t) * \sqrt{\left(\frac{1}{{PF_K^{operating}}^2} - 1\right)}, if\ leading\ PF \\ E_K^{active}(t) * \sqrt{\left(\frac{1}{{PF_K^{operating}}^2} - 1\right)}, if\ lagging\ PF \end{cases}$$

The actual operating power factor $PF_K^{operating}$ of the prosumer k is limited by the power factor limits:

$$PF_K^{leading-MIN} \leq PF_K^{operating} \leq PF_K^{leading-MAX}$$

$$PF_K^{lagging-MIN} \leq PF_K^{operating} \leq PF_K^{lagging-MAX}$$

The reactive energy in the local grid sums up, and the consumed reactive energy of inductive elements (lagging) cancels the supplied reactive energy of the capacitive elements (leading):

$$E_{grid}^{reactive}(t) = \sum_{k=1}^{N} E_K^{reactive}(t)$$

The active energy of the grid can be computed as the sum of the active energy produced, and its absolute values should be equal to the active energy consumed by the grid, to stabilize the frequency.

$$E_{grid}^{active}(t) = \sum_{k=1}^{N} |E_K^{active-generation}(t)| = \sum_{k=1}^{N} |E_K^{active-demand}(t)|$$

The power factor over the grid can be computed as the ratio between the reactive energy from the grid and the apparent energy in the grid, and it should be kept constant, at around 0.95.

$$PF_{grid} = \frac{E_{grid}^{reactive}}{E_{grid}^{apparent}} = \frac{E_{grid}^{reactive}}{\sqrt{(E_{grid}^{active})^2 + (E_{grid}^{reactive})^2}}$$

The optimization problem is defined in Figure 7, and has as inputs the set of distributed energy prosumers available to be considered in the VPP coalition and the target PF that must be achieved at local grid level. The solution of the optimization problem is a subset of energy producers located close to the imbalance point that can compensate the reactive energy.

The optimization objective aims at minimizing the distance between the actual power factor and the target power factor, as well as minimizing the distance between the grid elements that compensate the imbalance and the imbalance point:

$$\min\left(\sqrt{\sum_{t=1}^{T}\left(PF_{target}(t) - PF_{grid}(t)\right)^{2}}\right)$$

At the same time the VPP should gain profit by delivering this specific service:

$$\max VPP_{profit}^{PF} = Service_{Reward} - Gen_{cost}$$

$\boldsymbol{Inputs}: Prosumers\ [N], PF_{target}[T]$

$\boldsymbol{Outputs}: VPP\ –\ subset\ of\ prosumers\ which\ met\ the\ defined\ objective$

Determine

$PF_K^{operating}, VPP = \{taken_k | k \in \{1..N\}, taken_k \in \{0,1\}\}$

Such that

$\min\left(\sqrt{\sum_{t=1}^{T}\left(PF_{target}(t) - PF_{grid}(t)\right)^{2}}\right)$ and $\max VPP_{profit}^{PF}$

Considering the constraints expressed as equalities:

$$C1: E_{grid}^{active}(t) = \sum_{k=1}^{N}\left|(taken_k \vee active_k) * E_K^{active-generation}(t)\right| =$$
$$= \sum_{k=1}^{N}\left|(taken_k \vee active_k) * E_K^{active-demand}(t)\right|$$

$$C2: E_{grid}^{reactive}(t) = \sum_{k=1}^{N}(taken_k \vee active_k) * E_K^{reactive}(t)$$

$$C3: E_K^{reactive}(t) = \begin{cases} -E_K^{active}(t) * \sqrt{\left(\frac{1}{PF_K^{operating^2}} - 1\right)}, if\ leading\ PF \\ E_K^{active}(t) * \sqrt{\left(\frac{1}{PF_K^{operating^2}} - 1\right)}, if\ lagging\ PF \end{cases}$$

Considering the constraints expressed as inequalities:

$$C4: PF_K^{leading-MIN} \leq PF_K^{operating}(t) \leq PF_K^{leading-MAX}\ \forall t \in \{1..T\}, k \in \{1..N\}$$

$$C5: PF_K^{lagging-MIN} \leq PF_K^{operating}(t) \leq PF_K^{lagging-MAX}\ \forall t \in \{1..T\}, k \in \{1..N\}$$

Figure 7. Optimal VPP construction for offering spinning reserve modelled as CSP

4 Gradient enhanced heuristic optimization technique

As we have presented above all the prosumers coalitions in VPP optimization problems are modelled as CSP being classified as NP-complete. In all of them (see Figure 8) we aim at minimizing an objective function f having n real arguments and m integer arguments while fulfilling a set of k constraints of the form $c_i(x,y) \leq d$, knowing that each real and integer variable argument is bounded by a set of lower and upper limits.

Determine $x \in R^n, y \in Z^m$

$$minimize(f(x,y)), f: R^n \times Z^m$$

Such that

Constraints: $c_i(x,y) \leq d, i \in \{1..K\}, d \in R$

Variable Bounds: $x_L \leq x \leq x_H$

$$y_L \leq y \leq y_H$$

Variable Types: $x \in X \subseteq R^n$

$$y \in Y \subseteq Z^m$$

Figure 8. Optimization problem definition in a general manner

The optimization problem defined in Figure 8 is NP-complete, thus exact solutions are hard to find. Most state-of-the-art solvers leverage on approximation algorithms and heuristics to solve the problem. Basically, simpler problems, that have either only continuous (Nonlinear Programs – NLP) or just integer variables (Integer Linear Programming – ILP) are easier to solve. Classical solutions are based either on gradient-based optimization for NLP problems, using algorithms derived from gradient descent [29], while integer programming with bounded variables is tackled by various heuristics [30].

Table 2. Problem complexity considering variable types

x	y	*f-differentiable*	Problem Class	Algorithms
$x \in X \subseteq R^n$	$y \in \emptyset$	*yes*	NLP	Gradient-based
$x \in \emptyset$	$y \in Y \subseteq Z^m$	*no*	ILP	Heuristic-based
$x \in X \subseteq R^n\emptyset$	$y \in Y \subseteq Z^m$	*no*	MINLP	Hybrid Approach

The complexity of the mathematical problem that must be solved is strictly correlated to the variable types, as shown in Table 2. On the one hand, if the problem contains only continuous variables and the function f is differentiable, then gradient-based algorithms, such as the ADAM algorithm [24], can be used to compute an approximate solution. On the other hand, if the problem contains only integer variables, the f function is not differentiable, but heuristics can be applied to determine a solution by performing a search in the space of all feasible integer solutions bounded by the variable bounds y_L, y_H. The most complex case appears when the objective function f has both integer and continuous variables, because gradient-based methods cannot be directly applied while search heuristics in continuous space do not give good results.

We propose a hybrid approach that uses a heuristic to compute the integer variable values, fixes them as constants, making the f function differentiable, thus gradient-based methods being suitable to compute an approximate solution. The advantage of our approach is given by the potential to parallelize and decentralize the optimization problem computations to enhance the performance and decrease the time overhead. In case of a network of nodes capable of performing the computations (i.e. processing nodes located at each prosumer), the population of the algorithm can be split between the nodes, each of them running the gradient-based algorithm and then evolving its local individuals. At each round, the nodes communicate to exchange their local population, and each of them performs a ranking and a selection of the best individuals, generates a new population and distributes the best individuals to be ranked by the other nodes. Then, the population is split again between the processing nodes, and the gradient search is performed locally again to increase the computation speed.

Furthermore, to assure the immutability of the computation, the algorithm can be implemented over the blockchain distributed ledger. Even though the optimization problem is NP-complete, thus requiring a lot of processing power to solve, the verification and ranking of a solution can be done in polynomial time, thus by any node from the blockchain network, even if it has low processing power. To integrate the proposed algorithm with a distributed ledger, we will investigate in the next deliverable iterations two directions:

- The first direction involves having several peers with high processing power from the blockchain network running the algorithm as external services integrated with the blockchain using oracles. When a new coalition must be formed, these nodes compute one or several solutions, and the network chooses the best one and agrees upon it using consensus algorithms.
- The second direction involves building a consensus algorithm based on solving the optimization problem which is NP-hard. This involves proving that the optimization algorithm solving difficulty can be dynamically adjusted according to the number of miners from the network. We propose solving this issue by varying the population and the number of iterations of both the heuristic and the gradient solver.

The main steps of our hybrid optimization algorithm (see Figure 9) are the following:

- Apply a heuristic to determine a valid solution for the integer variables y;
- Set the integer values of y as constants in the function f. Now the function can be differentiated with respect to x;
- Apply a gradient-based method by iteratively improving the value of x considering the derivative of f with respect to x ($\nabla_x f$).

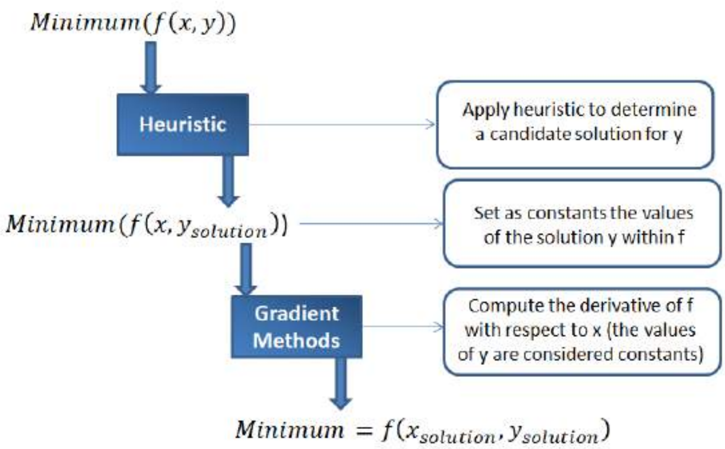

Figure 9. Hybrid optimization steps

However, this approach encounters issues due to the set of constraint functions c_i that must be verified by the values of the variables which minimize the objective function f. Thus, we define a new augmented objective function that will be minimized by the hybrid algorithms.

$$f_{objective}: R^n \times Z^m, \qquad f_{objective}(x,y) = < f_{constraint}(x,y), f_{barrier}(x,y)) >$$

The new objective function features two components:

- The first component is the number of constraints that are not met by a solution, computed as the sum of the cardinality of the set containing the indexes of the c constraint functions that do not meet the constraints (C_V) and the number of variable bounds that are out of limit

$$C_V = \{i|(c_i(x,y) > d\}|$$

$$C_X = \{i|x^i < x_L^i \lor x_H^i < x^i, i \in \{1..n\}\}$$

$$C_Y = \{i|y^i < y_L^i \lor y_H^i < y^i, i \in \{1..m\}$$

$$f_{constraint}: R^n \times Z^m, f_{constraint}(x,y) = |C_V| + |C_X| + |C_Y|$$

- The second component augments the function f with a set of barrier functions that consider the constraints from the set C_V which are not met. This is necessary in the cases when the constraints are not fulfilled due to their continuous component which is not modified by the heuristic based algorithm, and the gradient-based algorithm computes the same local optima which will not fulfil the constraints.

$$f_{barrier}: R^n \times Z^m, \qquad f_{barrier}(x,y) = f(x,y) + \mu \sum_{i=1}^{K} g_i(x)$$

Because the barrier function is applied only after the heuristic computes a solution for the integer components y, the functions g_i composing the barrier function have as argument only the continuous variables x. We define a function g_i for each constraint c_i which returns 0 if the constraint c_i is satisfied, otherwise the logarithm from the difference between the bound d of the constraint and the constraint value. To avoid having the argument of the logarithm in the interval [0,1], where the value of the logarithm is negative, thus leading to a decrease of the objective function even is the constraint c_i is not satisified, we add a 1 to the argument, thus constructing the term $\log(c_i(x,y) - d + 1)$.

$$g_i: R^n \to R, g_i = \begin{cases} 0, if\ c_i(x,y) \le d \\ \log(c_i(x,y) - d + 1), otherwise \end{cases}$$

The heuristic is a population-based search where multiple solutions are generated and evaluated based on the objective function. Two solutions are compared using the following comparator:

$$f_{objective}(x_1,y_1) \le f_{objective}(x_2,y_2)$$
$$\leftrightarrow \begin{cases} f_{constraint}(x_1,y_1) \le f_{constraint}(x_2,y_2) \\ OR \\ f_{constraint}(x_1,y_1) = f_{constraint}(x_2,y_2)\ AND\ f_{barrier}(x_1,y_1) \le f_{barrier}(x_2,y_2) \end{cases}$$

The proposed hybrid algorithm with generic heuristics and gradient algorithm is presented in Figure 10. The algorithm has as input a description of the optimization problem depicted in Figure 8, and as output a solution denoted as $sol =< x_{best}, y_{best} >$. The algorithm starts by generating a random initial population of candidate solutions, with random values for both x and y components within their bounds (line 1). Then, several iterations are performed, as shown in lines (2-9). Each iteration of the algorithm goes through the population and computes the x component using a gradient-based algorithm that computes the derivative $\nabla_x f_{barrier}$ of the $f_{barrier}$ functions with respect to x, after setting the values of the y variables as

y_{sol} computed by the heuristic (lines 3-5). Then, specific heuristic steps are applied, such as population rankings, selection and generation of new population (lines 6-8).

Input: Mathematical Optimization Problem Defined in Figure 8

Output: $sol_{best} =< x_{best}, y_{best} >$

Begin

1. $population$ = generate an initial population of candidate solutions
2. for (number of iterations)
3. $foreach(individual =< x, y_{sol} >$ from population)
4. $compute\ x_{sol}\ using\ gradient_{minimization}(\ f_{barrier}(x, y_{sol}))$
5. end $foreach$
6. $rank(population)$
7. $select(population)$
8. $population =\ generate_{new}(\ population)$
9. $end\ for$

End

Figure 10. Hybrid algorithm for mathematical optimization

As shown in the algorithm from Figure 10, the input is represented by an optimization problem instance having the form depicted in Figure 8. The main components of the problem are:

- the objective function $f: R^n \times Z^m$ that needs to be minimized;
- a set of k constraints c_i, in the form of expressions with expected results;
- a set of variable bounds for both the integer and the continuous variables.

Considering that the objective function and some constraints have the format of mathematical expressions which need to be evaluated or differentiated eventually, simply saving those expression as an array of characters is not enough. The chosen data structure is a binary expression tree, being a usual approach for representing mathematical expressions.

Table 3. Programming models used for representing mathematical formalisms in our approach

Mathematical Formalisms	Programming Models
Expressions: $f(x, y), c_i(x, y)$	Binary expression trees
Constraints: $c_i(x, y) \leq d, i \in \{1..K\}, d \in R$	Constraints in the form of mathematical expressions will be represented by pairs $(expression, operand, value)$, so that the value of the expression resulted by replacing the variables with given (x, y) values meets the operand applied to the given value. The operand can be equal, less than equal or greater than equal.
$x_L \leq x \leq x_H$ $y_L \leq y \leq y_H$	For constraints in the form of variable bounds, they will be represented by pairs $(variable, minValue, maxValue, integerType)$, where integerType is boolean variable which specifies if the variable is an integer or not.
$x \in X \subseteq R^n$ $y \in Y \subseteq Z^m$	Variables will be saved in a data structure in the form of a dispersion table, where the key will be represented by the variable and the value will be represented by the value of a variable at a certain time.

The binary expression tree can model two types of expressions: algebraic or logic. Furthermore, the expressions can contain unary operators (other functions – a trigonometric function as an example) or binary operators (addition, subtraction, multiplication, etc.). In an expression tree, the internal nodes are represented by operators and the leaves by numeric values or variables. The evaluation of expression trees is done recursively, starting from the root, and applying the operands from the internal nodes to the leaves.

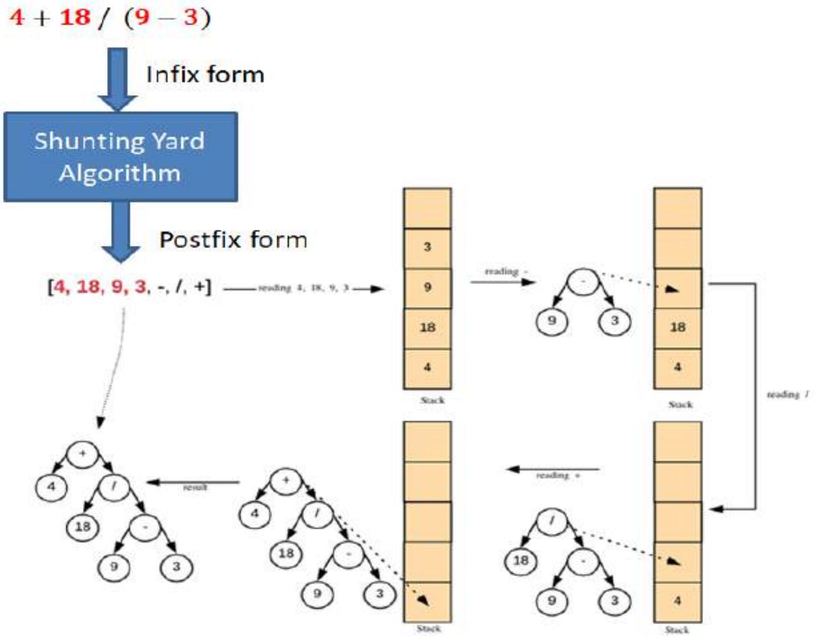

Figure 11 The construction of an expression tree

The procedure for constructing a binary expression tree is divided in two phases, and is depicted in Figure 11:

- transforming a mathematical expression from an infix form to a postfix form, which is done by applying the Shunting-yard method [27]
- transforming the resulting postfix form into a binary expression tree [28].

To compute the derivative of an expression tree, with respect to a variable, instead of computing the value of a node, we will apply the derivative, with respect to the type of node we wish to differentiate. We use the following notations:

- C is a constant value;
- S and T are two mathematical expressions;
- X is the variable with respect to which we differentiate;
- V is a variable different from X.

The rules of differentiation are presented in Table 4. The simplification of an expression tree is done during the process of differentiation, following which elementary nodes 0 and 1 can appear. Those are neutral elements in the operations used for this application, considering this, they can be simplified to avoid unnecessary computations and to increase performance.

Table 4. Differentiation rules

Rule	Expressions
Rule 1: The derivative of a constant or a variable different from the one with respect to which we differentiate is 0	$diff(C) = 0$ $diff(V) = 0$
Rule 2: The derivative of the variable X with respect to X is 1	$diff(X) = 1$
Rule 3: The derivative of the sum of S and T	$diff(S + T) = diff(S) + diff(T)$

Rule 4: The derivative of the difference of S and T	$diff(S-T) = diff(S) - diff(T)$
Rule 5: The derivative of the product of S and T	$diff(S*T) = S*diff(T) + T*diff(S)$
Rule 6: The derivative of the division of S and T	$diff(S/T) = \frac{T*diff(S) - S*diff(T)}{T^2}$
Rule 7: The derivative of S raised to the power of T	$diff(S^T) = T*S^{T-1}*diff(S)$

For the integer variables in the optimization problem the heuristic algorithm used was genetic algorithm. The algorithm evolves a set of individuals encoding the solution of the $y \in Y \subseteq Z^m$ integer variables that minimize the function $f(x,y)$. The population of the algorithm is defined as a set of P individuals.

$$Population = \{Individual_1, \ldots Individual_P\}$$

Each individual has a set of variables that provides a solution for the problem. Each variable is modelled as a chromosome, which in this case represents an integer variable. The chromosome, besides the value of the variable, contains the identifier of the variable, so that it may be correctly replaced in the solution (Figure 12).

$$Individual_i = \{Chromosome_1, \ldots Chromosome_m\}, Chromosome_j =< y_j.name, y_j.value >$$

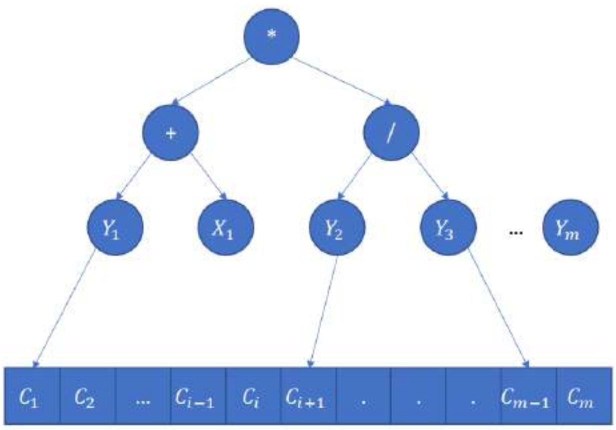

Figure 12. Mapping the integer variables Y from binary expression trees to chromosomes

The number of individuals should vary between one hundred and up to tens of thousands, depending on the complexity of the problem. In our solution, we have implemented three different types of initialization (see Table 5).

Table 5. Population initialization techniques

Type	Description
Fixed initialization	Each chromosome is initialized with a fixed value that is fixed in the code.
Random initialization	Each chromosome is initialized with a random value from a uniform distribution.
Given initialization	Each chromosome is initialized with a value from a given initial solution. This is also called a “warm start”.

After an initial solution is provided, each individual must be evaluated and ranked. The evaluation process consists of replacing in the evaluation tree the identifiers from the chromosomes with the value associated with them, and then evaluating the tree. Based on the value obtained by the evaluation, each individual can be ranked. The ranking is done based on the $f_{objective}(x,y) =< f_{constraint}(x,y), f_{barrier}(x,y)) >$ and the corresponding comparator defined on its two components.

After the individuals have been ranked, we can try and improve them by modifying them. The change in the set of individuals is provided by two mechanisms:

- Mutation – is the process where the chromosomes of an individual are modified to a different value. The mutation can change the value to a random one or add a small random value to the existing solution, to keep it in the same search space (Figure 13).
- Crossover – is the process where a set of the chromosomes of two individuals are interchanged. This results in two new individuals, one having the first part of chromosomes from the first individual, and the second part from the second individual, and the other having the first part from the second individual, and the second part from the first individual (Figure 14).

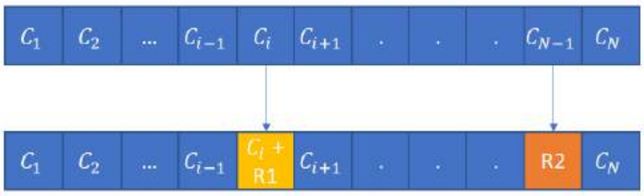

Figure 13. Mutation operation

Both these operations may provide a better or worse solution. Another proposed technique is generation of new individuals in each iteration, each individual generated having random chromosomes. This technique brings some variety to the population and it helps the algorithm to avoid local optima.

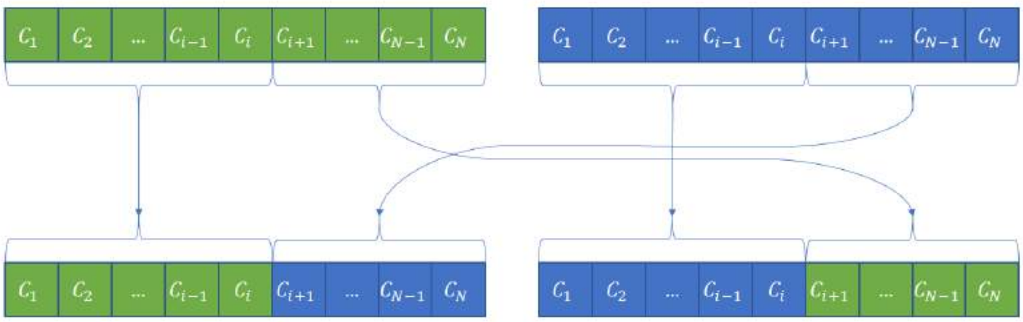

Figure 14. Crossover operation.

To preserve the best individuals, we also replicate the top 10% of individuals, and keep them untouched, not allowing mutation or crossover to happen. This allows us to both keep the current best solutions and tries and improve them with mutation or crossover to achieve a better solution.

After the existing population has been modified, we need to evaluate, rank and select the best individuals again. This cycle continues until the specified number of iterations is reached, or until no significant change is noticed in many iterations.

For the continuous variables of the optimization problem, a gradient-based algorithm was used. It uses the derivative with respect to x of the $f(x, y_{sol})$ function, where the integer variables that created discontinuities are replaced with fixed values determined by the genetic algorithm and considered constants each time the gradient algorithm is run.

Several gradient-based algorithms are used. To begin with, a stochastic gradient descent algorithm that relies on the derivative of the objective function is implemented. Based on the derivative, it will choose values in the neighbourhood of the current point where the function decreases. The recurrent formula is:

$$x_{n-1} = \mathrm{x_n} - \gamma \nabla f_{barrier}(\mathrm{x_n}, y_{sol})$$

where γ is a constant specifying the step, like a learning rate; the bigger the constant, the faster it will reach and area close to the optimum, but it will overshoot and bounce around, never reaching the optimum value; the smaller the constant, the slower it will reach the optimum, but it will not miss it. The $f_{barrier}$ function is defined at the beginning of Section 4 as an augmented version of the function $f(x, y)$.

A newer algorithm based on gradient descent, with better results is ADAM (adapted from *adaptive moment estimation*). It combines the advantages of two other algorithms based on stochastic gradient descent: AdaGrad [24] – an algorithm that works well for sparse gradients and RMSProp [25] – an algorithm that works well in non-stationary settings

5 Prototype implementation and evaluation

In this section, we will provide an implementation overview in regard to the eDREAM component that is dealing with the optimal construction coalitions of prosumers in VPPs targeting the delivery of specific services defined in Section 3. Figure 15 below shows a high-level design of the component showing the main technologies used for implementation.

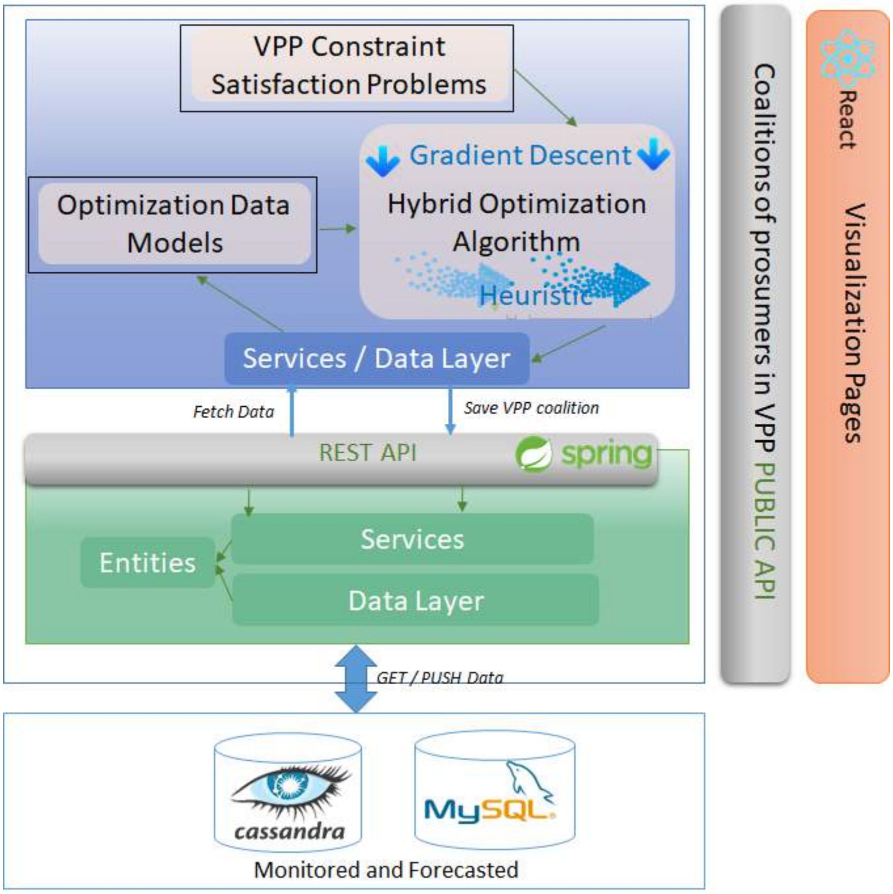

Figure 15. Hybrid optimization steps

The component has / uses the following modules:

- **REST API and Database** Layers– the role of this layer is to provide a unified REST API for components (including this one) to access the eDREAM distributed database. It is also used to validate and filter the incoming requests, providing an additional layer of security. This component contains:
  - Entity Module – contains OOP models mapped on the database structure
  - Data Layer Module – used for data access with predefined or custom queries
  - Service Module – used for data validation for the request or response of the layer
- **VPP Constraints Satisfaction Problems** – this module allows for describing and formalizing the creation of optimal coalitions of prosumer as a CSP using the model we have described in Section 3. At the same time, it offers the possibility to define and improve optimization problem goals tailoring them to existing or new services that need to be considered.

- **Optimization Data Models** – the module implements all the data models needed by our hybrid gradient enhanced heuristics optimization technique, such as the binary expression tree. It also implements the main mathematical operations needed in optimization such as functions derivation.
- **Hybrid Optimization Algorithm** – the module implements the gradient enhanced heuristic described in section 4. It solves the CSP problems for constructing optimal coalitions of prosumers in VPPs leveraging on the optimization data models defined.
- **Visualization pages** – a React JS [32] module that is used to provide a web-based graphical user interface. It provides a GUI over the Public REST API, to facilitate the access for users.
- **Public REST API** – used to expose the functionality of the module, such as energy trading, capacity bidding, spinning reserve or DR optimization problem solving (see Table 6).

Table 6. Public REST API of the component

Public REST API	
Construct VPP for energy trading	
Description	Through this interface, actors or other modules may post requests for the construction of a coalition of prosumers able to buy/sell a specific amount of energy from the energy marketplace also considering the energy price signal.
End-point URL	/vpp/energy-trading
Allowed HTTP Methods	POST

Request Body	{
	"prosumers": [{
	"prosumerId": "4836bee7-bc42-48a9-9e4e-aa1ecc68e6d8",
	"predictedProfile": { [
	{"value": 57167.566,
	"timestamp": "2018-09-08T00:00:00"
	},
	{
	"value": 57174.233,
	"timestamp": "2018-09-08T01:00:00"
	}, ...],
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	"predictionGranularity": "DAYAHEAD",
	"property": "ENERGY PRODUCTION"
	},
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	}
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	"type": "DEG"
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}</td></tr>
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}, ...]
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{"value": 157230,
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]
}</td></tr>
<tr><td colspan="2">Construct VPP for capacity bidding</td></tr>
<tr><td>Description</td><td>Through this interface, actors or other modules may post requests for the construction of a coalition of prosumers able to provide a replacement capacity on short notice.</td></tr>
<tr><td>End-point URL</td><td>/vpp/capacity-bidding</td></tr>
<tr><td>Allowed HTTP Methods</td><td>POST</td></tr>
<tr><td>Request Body</td><td>{
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	},
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	 }, ...],
	
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	 {"value": 157000,
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	 }, ...]
	 }
	 }

Response	{
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	 "selectedProsumers":[{
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	 "prosumerType": "DEG",
	 "biddedEnergy": [
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	 "value": 54412,
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	 },
	 {
	 "value": 57123,
	 "timestamp": "2018-09-08T01:00:00"
	 }, ...
	]

	}, ...] "totalEnergyBidded": [{"value": 136000, "timestamp": "2018-09-08T00:00:00" }, {"value": 150000, "timestamp": "2018-09-08T01:00:00" }, ...] }
Construct VVP coalition for providing spinning reserve	
Description	Through this interface, actors or other modules may request the dynamic construction of a VPP coalition of prosumers able to provide spinning reserve service on demand by activating or deactivating un-used capacity which can modify the reactive power.
End-point URL	/vpp/spinning-reserve
Allowed HTTP Methods	POST

Request Body	{
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	"predictedProfile": { [
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	"predictionGranularity": "DAYAHEAD",
	"property": "ENERGY PRODUCTION"
	},
	"uncertainty": {
	"min": 0.8,
	"max": 1.2,
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	"type": "DEG"
	}
	}, ...],
	
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	"priceSignal": [
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	"timestamp": "2018-09-08T00:00:00" }, {"value": 167000, "timestamp": "2018-09-08T01:00:00" }, ...] } }

Response	{
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	}, ...]
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	"timestamp": "2018-09-08T00:00:00"
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	{"value": 136000,
	"timestamp": "2018-09-08T01:00:00"
	}, ...
	]
	}

Construct VVP coalition for demand response	
Description	Through this interface, actors or other modules request the construction of a coalition of prosumers in VPP able to provide a requested target generation on demand.
End-point URL	/vpp/demand-response
Allowed HTTP Methods	POST

Request Body	{
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	{"value": 57167.566,
	"timestamp": "2018-09-08T00:00:00"
	},
	{"value": 57174.233,
	"timestamp": "2018-09-08T01:00:00"
	}, ...],
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	"deviceMeasurementId":"c0a735f0-b6fe-47e6-b951-79910cd0e822",
	"profileGranularityMinutes": 60,
	"predictionGranularity": "DAYAHEAD",

	"property": "ENERGY PRODUCTION"
	},
	"uncertainty": {
	"min": 0.8,
	"max": 1.2,
	"entityDeviceId": "ab7d658d-84cd-4662-b573-74db92a297f2",
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	"property": "Degradation-Trend"
	}
	"prosumerDetails": {
	"specification": {...}
	"type": "DEG"
	}
	}, ...],
	
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	}, ...]
	}
	}

Response	{
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	]
	}, ...]
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	},
	{"value": 140000,
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	}, ...
	]
	}

For evaluation we had conducted both qualitative and quantitative experiments to measure the performance of the proposed hybrid algorithm and capability of creating the dynamic coalition prosumers for some of the services defined.

We evaluated our hybrid gradient enhanced heuristic approach by comparing it with a state-of-the art commercial solver, Lingo Lindo [31], which uses a branch-and-bound technique for integer variables combined with a gradient-based method for computing the continuous variables. We implemented the VPP demand response CSP optimization problem in both Lingo and in our algorithm and compare the execution time and the best value computed for the optimization function. Several scenarios were generated featuring the parameters described in Table 7. We run in total 20 experiments, 5 experiments with $T = 8$ and $N = 50$, 5 experiments with $T = 8$ and $N = 75$, 5 experiments with $T = 8$ and $N = 75$ and 5 experiments with $T = 24$ and $N = 100$. For each group of 5 experiments, we computed the average running time of our solution, and for the Lingo solution.

Table 7. Parameters for solver evaluation

Parameter	Values
T – VPP construction and optimization future time window	8, 24
N – number of prosumers in local grid serving as base for the coalition construction	5, 75, 100
Number of scenarios run for each configuration	5
Prosumer energy values lower and upper bounds	$E_{Min} = 1\ kWh;\ E_{Max} = 10\ kWh$

The 1st set of experiments aims at evaluating the running time and the objective function minimum value determined by varying the number of prosumers aiming to determine the best coalition from a variable number of prosumers. We varied the number of prosumers N for three values: 50, 75 and 100. The results depicted in Figure 16 left show that for a fixed optimization time window of length T=8, gradient enhanced heuristic running time increases linearly, from 3400 seconds to 12000 seconds. The Lingo running time varies between 1 minute and 3 minutes. Figure 16-right shows the minimum value found by the algorithms, the Gradient Enhanced Heuristic being able to find a result with almost 50% better than the Lingo Heuristic. However, this comes at a cost of a running time increased with almost 10000%, thus being unsuitable.

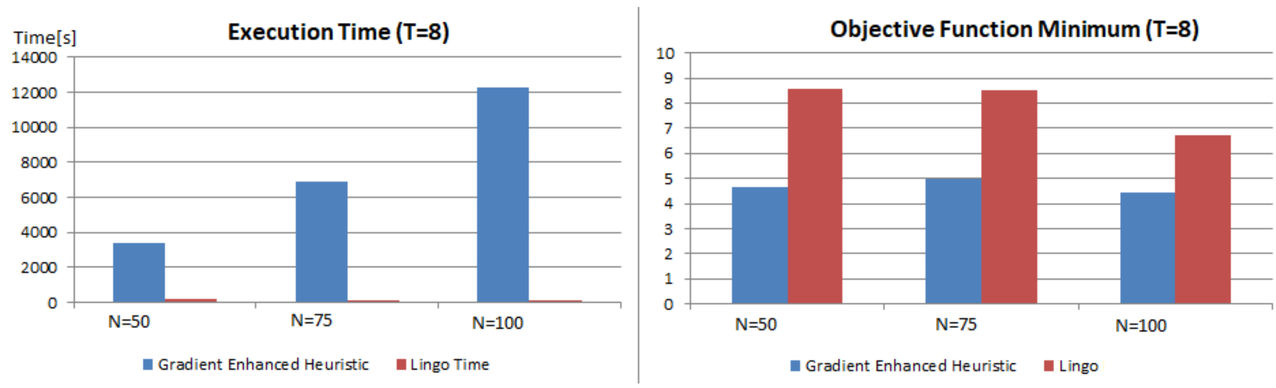

Figure 16. Gradient Enhanced Heuristic Vs Lingo – comparison for fixed time window size T = 8 (left-execution time; right – objective function minimum value)

The 2nd set of experiments aims at evaluating the execution time and solution quality for 100 prosumers. In this case, when the optimization window is 8, the Lingo gives better results, regarding execution time. However, when the optimization window time is increased to 24, the Lingo optimizer solving times increases more than the Gradient Enhanced Heuristic, even if the solution computed yields better result with 30% than the Gradient Enhanced Heuristic (see Figure 17).

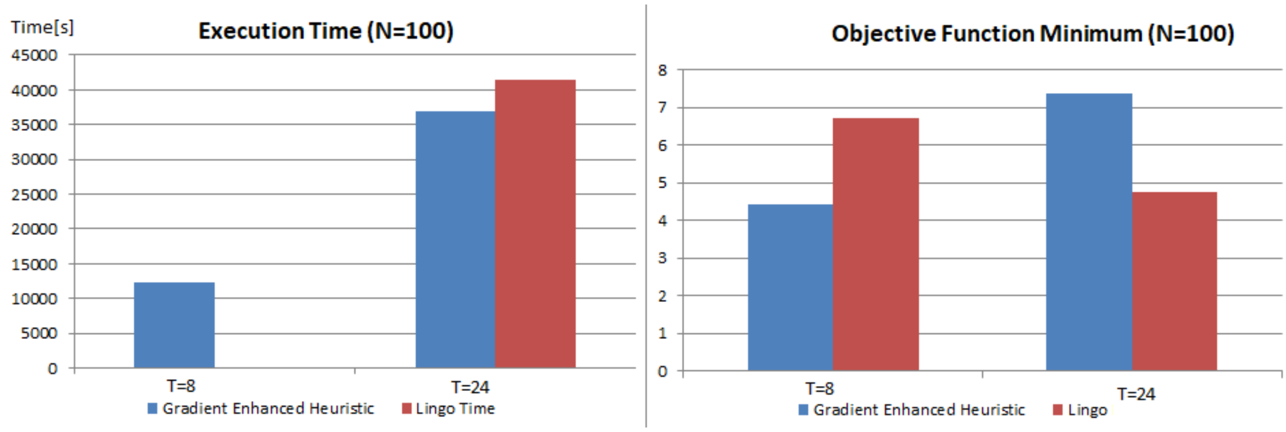

Figure 17. Gradient Enhanced Heuristic vs Lingo – comparison for fixed number of prosumers N=100 (left-execution time; right – objective function minimum value)

Considering the results shown above, the gradient enhanced heuristic has large execution time, but it manages to increase linearly with the problem size. The Lingo solver has very low running time and computes good solutions for small problem sizes. However, when the problem size increases, the Lingo solver has worse results than our approach.

The 3rd set of experiments aim to show our approach capability on solving the VPP specific CSP problems and generating the prosumers coalitions tailored to the specific services constraints. In particular, we aim to determine the sub set of prosumers such that they can provide an aggregated energy generation that follows closely a requested curve time window of 24 hours provided by a third party such as the DSO.

In our scenario we have considered a pool of N=50 prosumers from which the optimal subset forming the coalition need to be selected. For each prosumer a 24 hour-ahead energy generation profile E_k is used. Figure 18 shows the 50 prosumers profiles.

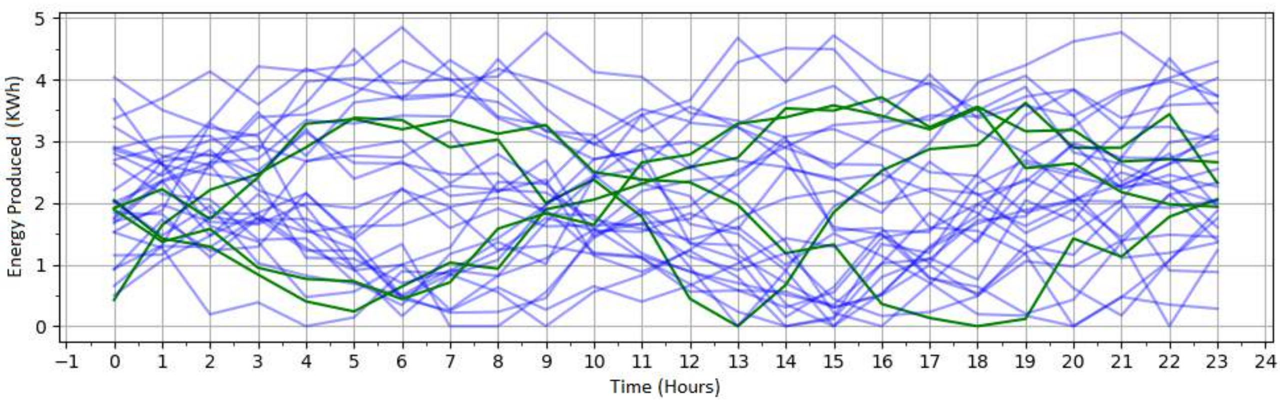

Figure 18. Prosumer portfolio from which the VPP coalition will be created

Figure 19 top presents the requested energy generation profile coloured in red and total energy produced by the VPP coloured in green which was dynamically created from a coalition of 4 prosumers (selected out of 50 available) to optimally match the request. The Figure 19-bottom shows the disaggregation of the coalition composed from individual prosumers taken from the prosumer pool shown in Figure 18. The dynamically created coalition manages to follow the requested generation curve with an accuracy of 9.31%, by selecting a subset of 4 prosumers from the pool of 50 prosumers.

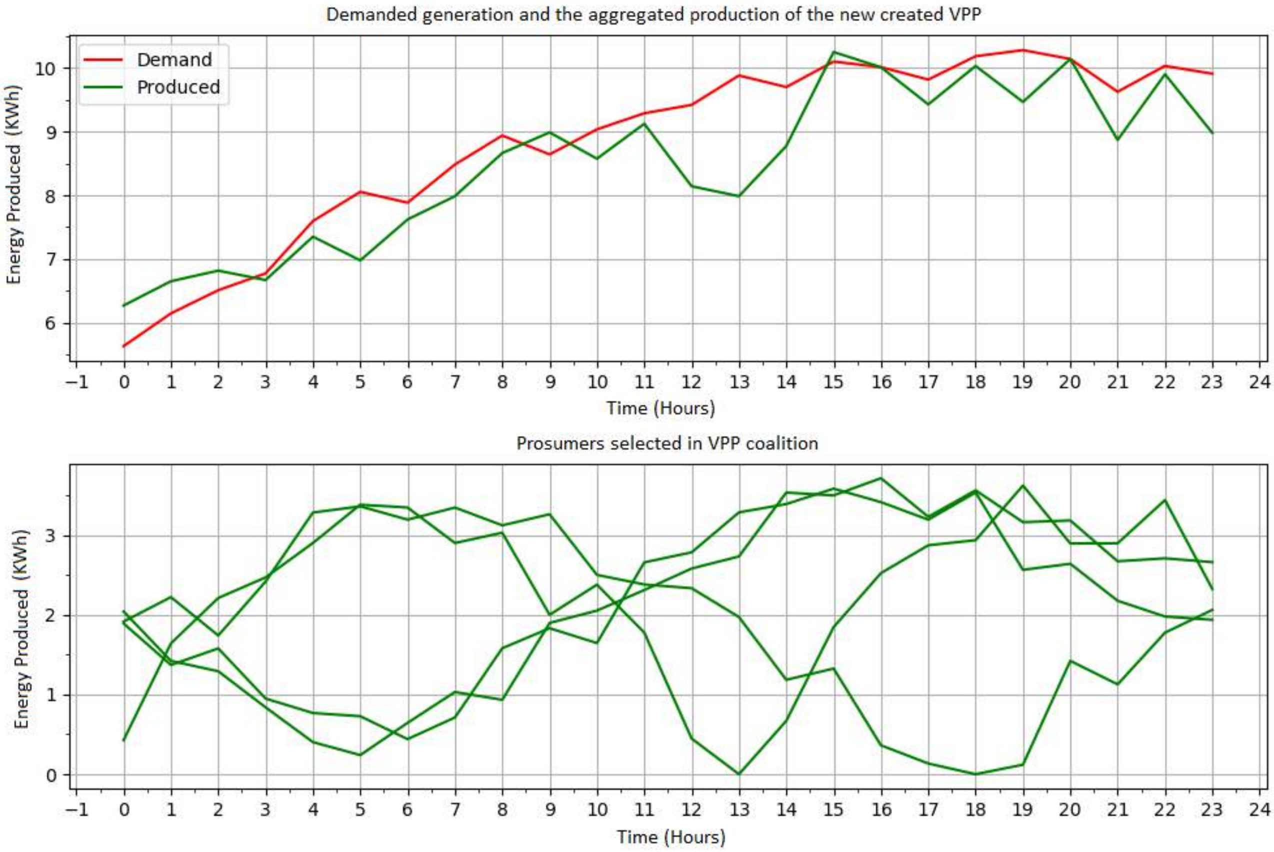

Figure 19. VPP coalition formation (top- requested generation profile and VPP total energy produced; bottom – energy profiles of selected prosumers as part of new created VPP coalition)

The 4th set of experiments corresponds to the VPP energy Trading Service Optimization Problem defined in Figure 4 meaning the trading of energy for maximizing the participants profit. The portfolio of 50 prosumer out of which the VPP will be constructed have the 8 hour generation profiles depicted in Figure 20.

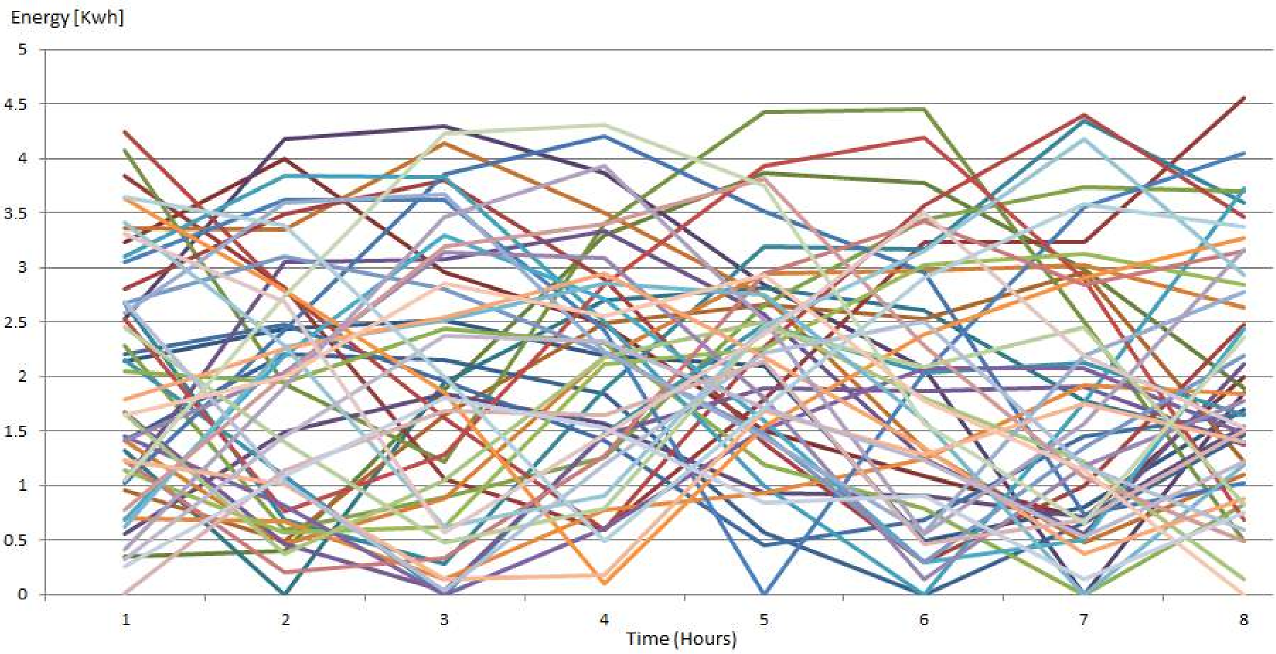

Figure 20. Portfolio of prosumers. Energy generation over 8 hours' interval

Thus we are aiming to determine a subset of energy prosumers from the portfolio able to deliver an energy amount proportional with the energy prices depicted in Figure 21-left over a 4 hour time interval. In the first 2 hours the energy price is low, while during the last 2 hours the energy price increases while the total energy generated by the portfolio of prosumers without optimization, depicted in Figure 21-right, shows that more energy is generated while the price is low.

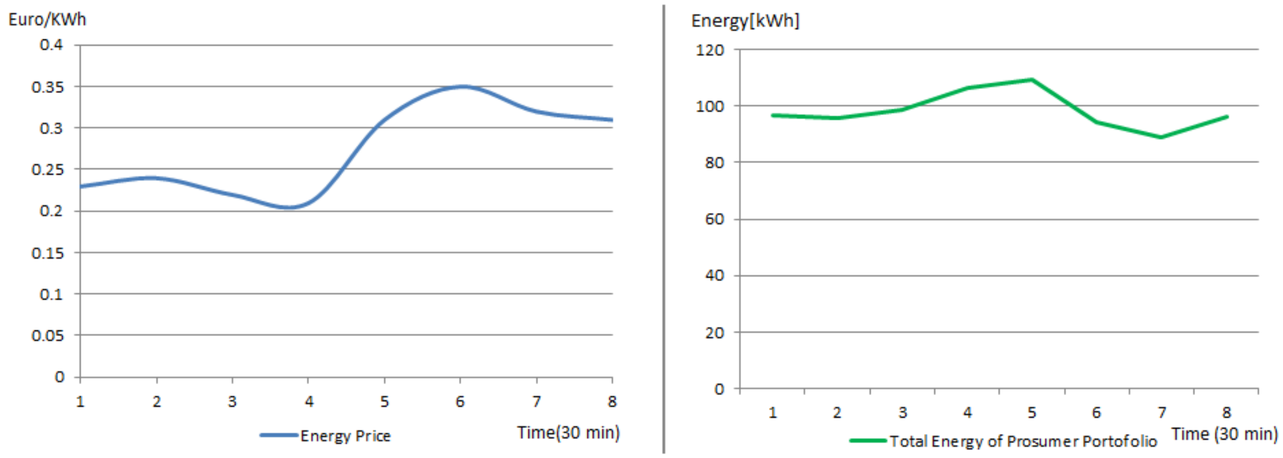

Figure 21. Energy Price over a 4-hour time interval (left) and total energy of the prosumer portfolio (right)

Thus, in the coalition the prosumers that produce more energy in the second part of the optimization interval would be selected, leading to an increase of their profit compared to the initial revenue received if they would sell their energy as produced. Furthermore, by having a smaller set of prosumers, they can also use the batteries from the system to store energy when the price is low, and sell it when the price is high. We model a set of batteries with the total capacity of 30 kWh, and a charge/discharge cost of 0.1 euro/KWh for a maximum Depth of Discharge DoD = 40% (computed considering a battery price of approximately 200 euro per KWh and 2000 life cycles) and a charge-discharge loss of 15%.

The Virtual Power Plant coalition can be seen in Figure 22-left. The total energy generated by the power plant follows the energy price profile to maximize the profit. A number of 7 prosumers were selected, with the average revenue with over 40% higher for each prosumer, compared to the initial values. The battery was used to store energy when the price was low, as shown in Figure 22-rigth, and discharged when the energy price started to increase.

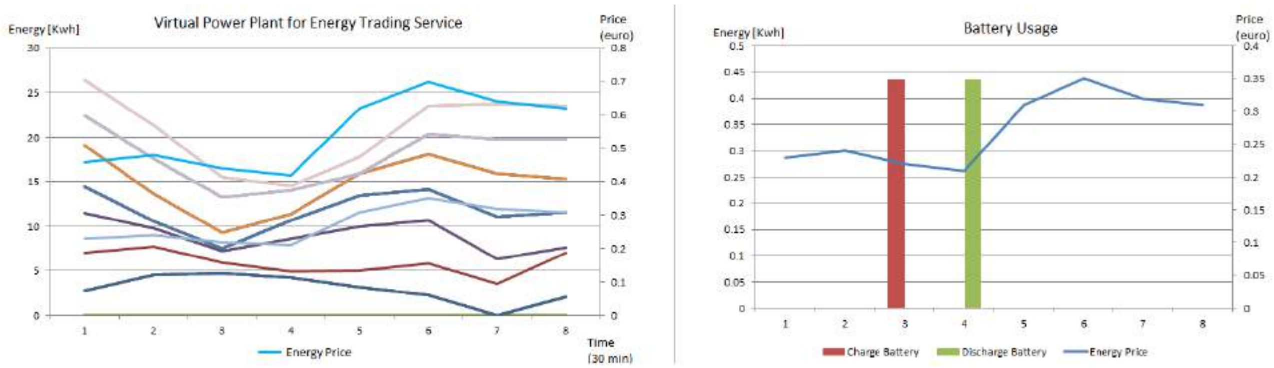

Figure 22. VPP coalition created for trading energy (left); Battery usage during coalition optimization interval (right)

<u>The 5th set of experiments</u> corresponds to the optimization problem defined in Figure 5, that aims at determining a subset of prosumers that can offer target capacity level during a 4 hour time interval. We aim at selecting the best fitting prosumers from the portfolio depicted in Figure 20 that can offer a constant 15kWh capacity.

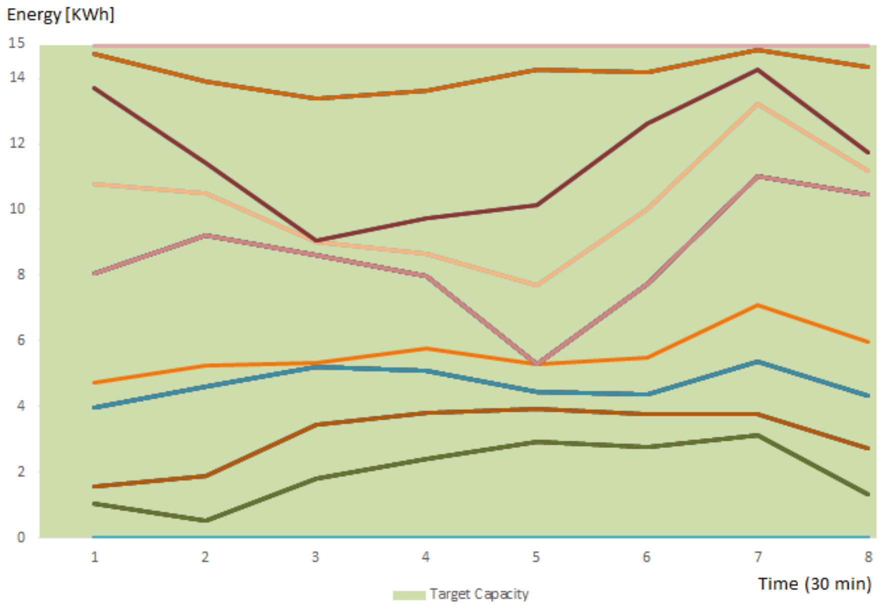

Figure 23. Virtual Power Plant Coalition for Capacity Bidding Service

The coalition formed by the 9 selected prosumers to offer the 15 kWh capacity over the 4 hour time interval is depicted in Figure 23, showing that the stacked energy profiles cover the energy area coloured in green of the requested capacity.

6 Conclusion and future work

In this deliverable, we had proposed a VPP model which allows us to formalize the problem of dynamic construction of optimal coalitions of prosumers in VPPs as a constraint satisfaction problem which can be tailored and adapted to different types services the new constructed VPP may offer. Using our model, we have defined the dynamic construction of VPPs for different objectives, such as to trade energy in day ahead and intraday, to sell on short notice replacement capacity to a power plant, which can't meet its commitment, to provide frequency regulation committing unused capacity and to meet specific energy generation requests. At the same time, we had proposed a hybrid optimization technique, which combines the gradient-based solutions with nature-inspired heuristics for achieving fully distributed platform for creating prosumers coalitions. Our solution time complexity scales linearly with the number of prosumers to be considered in the optimization problem compared with the state-of-the-art approaches. This is very important, eDREAM targets to aggregate many small-scale prosumers facilitating the participation through the VPP of small-scale producers as little as 1 kWh capacity generation. The evaluation results are showing our approach feasibility in constructing coalitions for optimal trading of energy, capacity bidding and VPP DR optimization.

In the next deliverable iteration, we aim to refine and improve the defined CSP optimization problems for various type of services the VPP may provide, to formalize the optimal coalition formation to other types of services and to investigate the potential of hybrid heuristic to be decentralized and run over blockchain based infrastructure. In the blockchain integration case, we will aim to investigate two directions: running the hybrid optimization algorithm as external service integrated with the blockchain using oracles and building a consensus algorithm based on solving the optimization problem which is NP-hard one.

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