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OPTIMIZATION BY STOCHASTIC PROGRAMMING FOR THE AGGREGATION OF A COMMERCIAL VIRTUAL POWER PLANT

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Abstract. Future large penetration of Distributed Energy Resources (DER) leads to explore the potential of technical integration of these dispersed small-size generators into the distribution network. New actors may emerge, devoted to the commercial or technical aggregation, in order to provide ancillary services or to gain global productivity. Aggregating a set of small producers into a commercial Virtual Power Plant could enable its market participation like a conventional power plant. The function of aggregation should be able to reduce imbalance risk in the market, by the means of an existing methodology based on stochastic programming. This methodology is described and extended to new generation characteristics, with a discussion about the necessary improvements and about its application to a real-size case, on a rural alpine area.

Keywords: Day-ahead energy market, Distributed Energy Resources, imbalance penalties, steady state aggregation, stochastic programming, Virtual Power Plant.

NOMENCLATURE

CDF: Cumulative distribution function
CVPP: Commercial Virtual Power Plant
DER: Distributed Energy Resources
DG: Distributed generation
DSO: Distribution System Operator
ED: Economic Dispatch
HV/MV: High Voltage / Medium Voltage
MCP: Market Clearing Price
PDF: Probabilistic density function
RV: Random variable
SBP: System Buy Price
SSP: System Sell Price
TSO: Transport System Operator
TVPP: Technical Virtual Power Plant
UC: Unit Commitment
VPP: Virtual Power Plant

INTRODUCTION

With the increasing penetration of Distributed Generation (DG) and the liberalization of the energy market, there are opportunities to the emergence of new actors and innovative structures on the transmission and distribution networks. One of these new concepts is the aggregation of DG and eventually, reportable loads, into a controllable Virtual Power Plant (VPP). Such a virtual power plant aggregates the capacity of many diverse DER: it creates a single operating profile from a composite of the parameters characterizing each DER. Due to this aggregation, the individual participants would reach the size and the characteristics of a transmission-connected conventional producer, allowing them to access to the energy markets and to provide ancillary services to the network operators. Two kind of VPP are ordinary considered: the Commercial VPP (CVPP) and the Technical VPP (TVPP) with distinct roles [1] [2].

The new concept of aggregating a portfolio of DER requires coordinated management and control tools. A same DER can be part of both a CVPP and a TVPP. Within a CVPP, the energy provided by a producer can be sold to the wholesale market. The TVPP focuses on the network operation aspects. The TVPP is a part of the distribution network control system: it is composed of all the DER units of a distribution network area, fed from the same HV/MV substation. One of its functions is to perform the validation of the day-ahead base schedules of all the locally interconnected DER units. In contrast, the impact on the distribution network is not considered in the CVPP operations. As a commercial VPP is composed of a portfolio of DER, with various generation characteristics, operating patterns and availability, the function of aggregation of characteristics is a key issue in evaluating the potential of market participation and in optimizing the revenue from contracting DER portfolio output. This paper focuses on the specific functions required within a Commercial VPP, and more precisely, on the question of the method of steady state aggregation of a portfolio of DER into a commercial plant on the day-ahead market, following the imbalance penalties fixed by the market mechanisms [3]. This aggregation supposes a compromise between the risk of a contracted volume position and its expected benefits: it can be successfully expressed as an optimization problem.

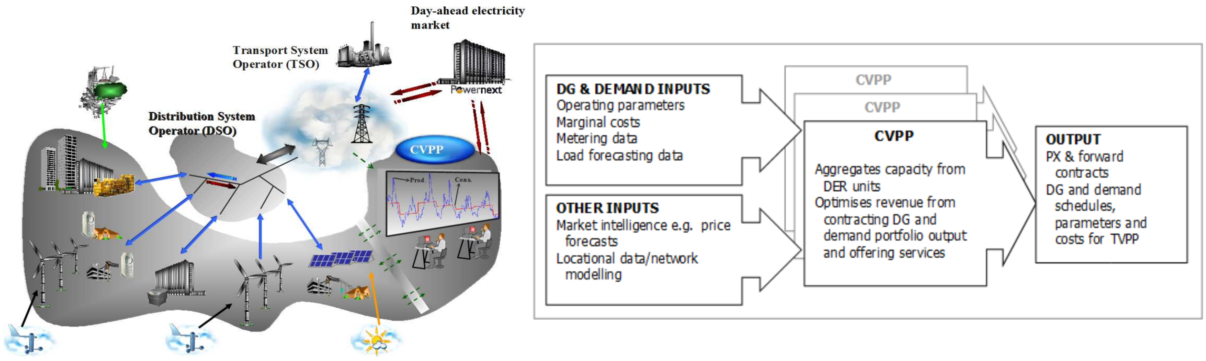

Figure 1. Inputs and outputs of the CVPP activities (from [7])

In power system operation and planning, there are many optimization problems that search, for the next 24 hours or a smaller time horizon, solutions to determine the optimal production resources required at minimum cost within a set of constraints. This scheduling is done over time (hours, days, etc). These methods are well-known, with an abundant research literature. For example, the hourly commitments of units, the decision whether a generation unit is on or off at a given hour, is referred to as *Unit Commitment* (UC). Daily or hourly production of various types of available generation plants is called the *Economic Dispatch* for all-thermal units (or the *hydrothermal dual problem* when it takes into account the flexibility of being able to manage water reserve levels) [4] [5] [6]. There are some common points: the expression of the function objective; the characteristics of the generation unit models; a time discretization of the scheduling operation variables.

The CVPP aggregation problem differs by two main aspects. Firstly, there is no demand constraint: the optimal produced energy is dependent rather from the market price value, issued from the entirely external market fixing process. Secondly, the main limiting factor of the participation of individual small-scale DER in the day-ahead market (as we assume the total production capacity of the portfolio reaches the minimal size fixed by the market regulation authority) is a consequence of the uncertainties related to the output of the individual DER: a single producer cannot afford the cost and the risk of paying imbalance penalties. Therefore, it is necessary to include these uncertainty parameters. By aggregation of all generation characteristics and uncertainties, the performance of a portfolio of DER on the day-ahead market can be optimized, whatever the future electricity market clearing price will be.

The energy exchange market is assumed to be a day-ahead market. The participants of the day-ahead market send their offers to sell and buy a specified amount of energy, for each hour of the next day. Then, at the daily fixing time, the blind fixing process occurred, operated by the coordinating authority: the hourly individual supply bids are sorted out, according to a growing marginal cost, and aggregated into a total supply function; reciprocally, the hourly aggregated demand function is built from the sorted supply bids. The hourly marginal price is calculated by linear interpolation, as the intersection between these two functions. This marginal price determines the hourly Market Clearing Price (MCP) and consequently, the set of accepted and rejected bids.

COMMERCIAL VIRTUAL POWER PLANT AGGREGATION METHOD

Assumptions: CVPP on the day-ahead wholesale market

The following assumptions are necessary to formulate the model of optimal aggregation of the characteristics of the DER portfolio:

- The generation characteristics of the CVPP portfolio and the probability distributions of all random parameters (relative to the production part) are supposed to be known by the CVPP dispatcher;

- Because of its accepted supply bid for the next day, the CVPP enters into contractual agreement to produce a certain volume of energy, and is exposed to the system balancing penalties. The CVPP is charged System Buy Price (SBP) for each MWh short of its contractual obligation; reciprocally, the CVPP is paid System Sell Price (SSP) for each MWh produced in excess of its contracted quantity. It will be assumed that the day-ahead price lie between System Sell Price and System Buy Price: $SSP \leq MCP \leq SBP$ *;*
- The portfolio aggregation maximizes the expected profit for each possible value of market clearing price.

The set of assumptions, concerning the market price and balancing mechanisms, are consistent with the rules of the French day-ahead electricity market EPEX Spot (previously POWERNEXT [3]). About the last assumption, risk-aversion preference is not considered here, in a first step. Moreover, the CVPP is supposed to have a limited and marginal capacity size, and then to be only a price-taker agent: its participation cannot substantially influence the fixing process of the hourly market clearing price, contrary to an oligopolistic agent.

Formulation of the problem

A previous study by Imperial College, within the European project FENIX [7] [8], proposed a formulation of the anticipated position of the portfolio, as a *stochastic programming problem*. This term refers to a problem class, and not to a choice of solution procedures. The use of stochastic programming is quite common in energy systems, dealing with unavoidable uncertainty. In this case, such kind of stochastic problems can be expressed as a two-stage stochastic mixed integer linear problem, with a classical formulation:

$$(1) \qquad \min z = c^T x + E_{\xi}\left[\min q(\omega)^T\, y(\omega)\right] \qquad \text{s.to} \qquad \begin{aligned} & Ax = b \\ & T(\omega).x + W.y(\omega) = h(\omega) \\ & x \geq 0, \quad y(\omega) \geq 0 \end{aligned}$$

The interpretation of this expression is the following: the two-stage type refers to the number of time instances when the aggregator should take a decision (optimized by minimization). With its participation in the day-ahead market, the CVPP supervisor enters into contractual agreement to sell a certain quantity of electricity at a certain price (this bid is the first-stage of decision). The next day, during the concerned hourly period, the random events ω have been occurred (unavailability of a generator) – or are occurring (real-time intermittent power production output, different from the forecast value). Then the second-stage of decisions has to be made, by the means of corrective actions (load-following use of the available dispatchable generators): this second-stage problem is a deterministic optimization problem. The *stochastic programming* has the following goal: first-stage decision should be made taking into account its future effects, knowing the probabilistic distribution of the random events, and the expected performance of the corrective actions in each case.

By superimposing all possible values of the available capacity of the individual DERs, with fixed market prices at a certain time, it is possible to construct a number of combinations, which in the context of stochastic optimization are called *scenarios*. The expected profit in each of the scenarios is found as the difference between the expected revenues from the day-ahead market on one side, and expected net payments in the balancing markets and expected generation cost on the other.

$$(2) \qquad \max_c \; REV = \max_c \; (R_{MCP} + R_{\cos ts})$$

$$(3) \qquad REV = R_{MCP} + R_{\cos ts} = c \cdot MCP + E_{\omega}\left(DP^{+}(\omega)SSP - DP^{-}(\omega)SBP - \sum_{i=1}^{N} Pg_i(\omega).CG_i \right)$$

where DP^+ and DP^- represent the surplus or lack of energy ($DP^+, DP^- \geq 0$) as compared to the contracted amount (c), and Pg_i is the second-stage decision variable describing the generation level of generator i in the future period. Each generator is characterized by a constant value of production cost CG_i ; it is assumed a constant efficiency, with respect to the produced power. The terms DP^+, DP^- and Pg_i are second-stage variables, and depend on the outcome of the random event values ω. E_ω here denotes mathematical expectation with respect to the probabilities of individual random events ω.

$$(4) \qquad DP^{+}(\omega) = \max(0; \sum_{i=1}^{N} Pg_i(\omega) - c) \quad \forall \omega$$

$$(5) \qquad DP^{-}(\omega) = \max(0; c - \sum_{i=1}^{N} Pg_i(\omega)) \quad \forall \omega$$

Offer quantities for the day-ahead market are then sought with respect to the maximum expected profit across all scenarios and their relative probabilities.

Study cases

This formulation has been re-used and then extended to more various characteristics of generation, especially with diverse active power loading capability. A new resolution is proposed too for the specific case of a portfolio composed by a mix between several conventional small generators and intermittent renewable energy sources.

The approach described in the previous section will be demonstrated on three study cases from [7], re-used here in order to validate the results. Case A includes only conventional distributed generators that exhibit uncertainty through the possibility of suffering a power outage. In other words, each generator at the time of delivery can be found in one of two states – either fully available or unavailable, with the assigned probabilities. In Case B, an intermittent generator or a set of intermittent generators (for example, a wind park) is exposed to the day-ahead and balancing markets. As its production for the next day is hourly forecasted, the uncertainty of the generation output is modeled through the random variable of production power, with a normal probability distribution function (PDF). Case C represents the combination of A and B, i.e. a portfolio combining both conventional and intermittent generators. The same values of conventional generator capacities and state probabilities are retained to enable comparison between cases. The data on the generators for all cases are summarized in Table I. Conventional generators are characterized by their capacity, operating cost and availability, with total capacity of 30 MW.

Table 1. Portfolio generator units characteristics – cases A – B - C

Generator characteristics - Case A: Conventional generators – source: [7]			
No.	Nominal capacity (MW)	Gen. cost (€/MWh)	Availability (%)
1	5	50	65
2	10	40	70
3	8	45	55
4	7	48	60

Case B – Intermittent generator		
No.	Output (MW)	Standard deviation
1	30	9 (– 4,5)

Case C – Mixed - idem case A + Intermittent generator with following characteristics:		
No.	Output (MW)	Standard deviation
1	15	2 (– 1)

Default prices used in this example are: *MCP* = 60 €/MWh, *SBP* = 100 €/MWh, *SSP* = 20 €/MWh

RESULTS

Results - case A

Case A: the characteristics of a portfolio of "conventional" all-thermal generating units are described in Table I from [7]. As there are in total four generators with possible unavailabilities, the number of different combinations of available/unavailable generators is $2^4 = 16$ scenarios. In the initial formulation, there is no generating constraints (case A-1): the unit can produce in an active power range from 0 to the nominal capacity, at the same efficiency.

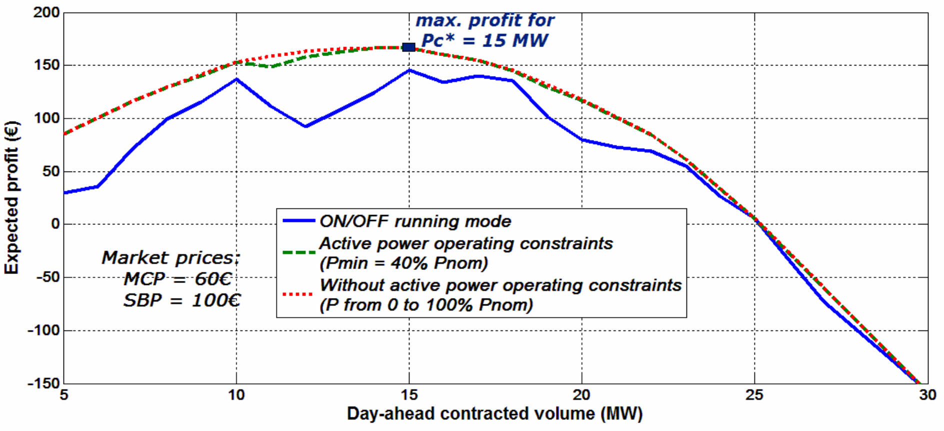

Figure 2. Expected profit of the portfolio as a function of contracted volume

This initial set of portfolio characteristics has been re-used and then extended to other characteristics of generation, with diverse active power loading capability: A-2) with active power operating constraints (default values of minimal generating power assumed to be 40% of the nominal power) and A-3) on/off running mode. Both generation characterization modes change the nature of the second-stage decision variables, and consequently, impose a second-stage resolution respectively, by *integer programming* and by *mixed integer linear programming*.

If the expected profit across all scenarios is calculated for a whole range of contracted quantities, the dashed red line in Figure 2 is obtained. By using the stochastic approach, without power operating constraints, one gets the value of 15 MW as the optimal solution for the contracted volume, with an expected profit of €166.3 per hour. We can observe the intuitive result that, better are the load-following capabilities of the four conventional generators of the portfolio, higher is the expected performance, as shown in Table 2.

Table 2. Results (case A) for default price values

	Case A-1 *Without constraint*	Case A-2		Case A-3 *On/Off*
		Pmin:40%	*Pmin:80%*	
Optimal contracted volume (MW)	15	15	15	15
Corresponding expected profit (€)	166,3	166,3	162,7 *(-2,2%)*	145,3 *(-7,2%)*

Same multiple curves are obtained by varying the value of market clearing price *MCP*. On each curve the highest point is marked as the optimal contracted volume (c^*). As the expected profit can be maximized for each market clearing price and imbalance penalty price, then it is possible to calculate optimal contracted volumes for a whole range of day-ahead prices. This information would then enable the construction of the portfolio's supply curve, determining the offered quantity for each level of day-ahead price. The step-wise supply curves are drawn for several values of imbalance penalty price (*SBP*). The result is identical to [7].

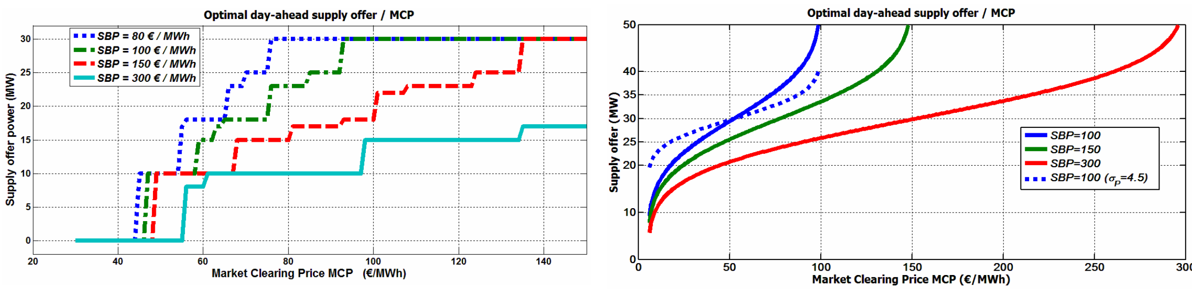

Figure 3. Optimal contracted volume vs. market clearing price value – case A-1 (left) , case B (right)

Results – case B

Similarly to the conventional DER case, it is assumed that the generator (or a group of generators) with capacity P_{max} has to enter into a contract to sell its output for the following period in the day-ahead market. The data available to the operator are its expected output P_E, and the forecasting error (standard deviation) of the expected output σ_P. It will be assumed that the forecasted plant output P is a random variable with a normal distribution and parameters P_E and σ_P: $P \sim N(P_E, \sigma_P)$.

This means that its probability density function (PDF) is given by:

$$f(x) = \frac{1}{\sigma_P \sqrt{2\pi}} e^{-\frac{(x-P_E)^2}{2\sigma_P{}^2}} \tag{6}$$

The initial study [7] proves that an exact analytical resolution is possible since P is a normally distributed variable. The optimal contracted quantity reaching the maximum of the objective function is given by the following formula:

$$c^* = \Phi^{-1}\left(\frac{MCP - SSP}{SBP - SSP}\right) \tag{7}$$

with $\Phi(x) = P(P \le x)$, its cumulative distribution function (CDF), which represents the probability that the random variable P takes the value less than or equal to x; $\Phi^{-1}(p)$ denotes the inverse of Φ, representing the value that P is less than or equal to with a given probability p. Like for the case A, it is possible to calculate optimal contracted volumes for a whole range of day-ahead prices.

The Figure 3 (right) where step-wise supply curves are drawn for several values of imbalance penalty price (*SBP*), is identical to the results in [7]. Dashed lines in Figure 3 describe the situation when standard deviation of wind output distribution is smaller (i.e. 4,5 MW compared to 9 MW). As expected, the curve of optimal contracted volume shows greater variations when the relevant standard deviation is larger.

Results – case C

By combining the analysis for conventional and for intermittent generators, it is also possible to characterize a portfolio consisting of intermittent DER generators and conventional generators with controllable output. Again, it is assumed that the total output of the intermittent generation part is a normally distributed random variable with mean value P_E and standard deviation σ_P

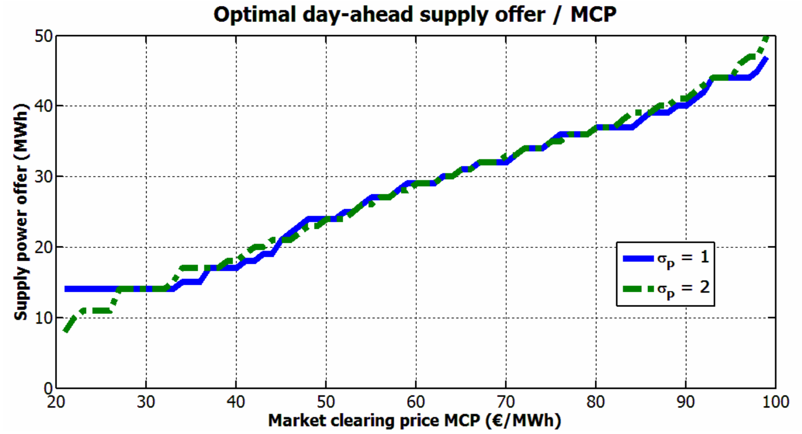

Figure 4. Optimal contracted volume vs. market clearing price value – case C

As an exact analytical resolution is not possible in this case, a discretization of the PDF function is applied. It has been verified for the cases B and C that even a limited number of interval values (around 8-13) is sufficient to reach an acceptable precision (< 0,5%) and then, to avoid a multiplication of useless calculations. A process of verification with an increasing number of variation intervals of PDF values shows a rapid convergence of the maximal expected profit and the corresponding optimal contracted volume. Like the other cases it is possible to determine the optimal supply curve (see Figure 4). It can be seen that different standard deviation values of the intermittent power output do not change significantly the optimal contracted volume curve in function of the market clearing price.

DISCUSSION

Contributions of the work

The methodology to calculate optimal contracted volumes for a whole range of spot prices by stochastic programming has been successfully applied: a portfolio aggregator can determine its optimal supply curve (price vs. quantity), in order to reach the maximal expected profit on the market. With this method, the influence of each input parameter and of each generator unit can also be examined. The method has been extended to include generating constraints of thermal-type units. A new resolution has been proposed too for the specific case of a portfolio composed by a mix between several conventional small generators and intermittent renewable energy sources.

The final goal of the CVPP portfolio aggregation is the definition of the optimal supply bid. Therefore, an additional step of linearization of the supply curve is necessary: the CVPP will offer a step-wise supply bid with increments of supply power at different growing prices. This step-wise supply bid has to approximate at the best the aggregated supply curve as function of day-ahead price.

Otherwise the simulation of the different cases show that the value of the System Buy Price is very influential (contrary to *SSP* which is of little influence, as long as it is lower than individual generation costs, since it is not reasonable to expect that the portfolio owner, once the availability status of its generators is known, would use them in such a way to generate more than the contracted volume). SBP corresponds to one of the imbalance prices which are known only after realization of the day: it seems essential to include now the uncertainties about SBP values. This can be easily done, if there is some information on the probability distribution of this price, relatively to the day-ahead market clearing price. In such a case, there will be price scenarios too during the aggregation calculations. An example of result (case A – MCP = 60€) is shown in Figure 5. The grey curve represents the optimal contracted volume: as the short imbalance overcost (SBP minus MCP) is small, it is more interesting to offer a greater supply power quantity, but this position will be riskier: the gradient of the expected profit is higher too. The final choice of the volume position will depend on the risk preference strategy of the CVPP aggregator. For example, the function objective could be modified, by addition of a negative penalty term, relative to the risk of the day-ahead contracted volume position, with respect of a variation of imbalance prices.

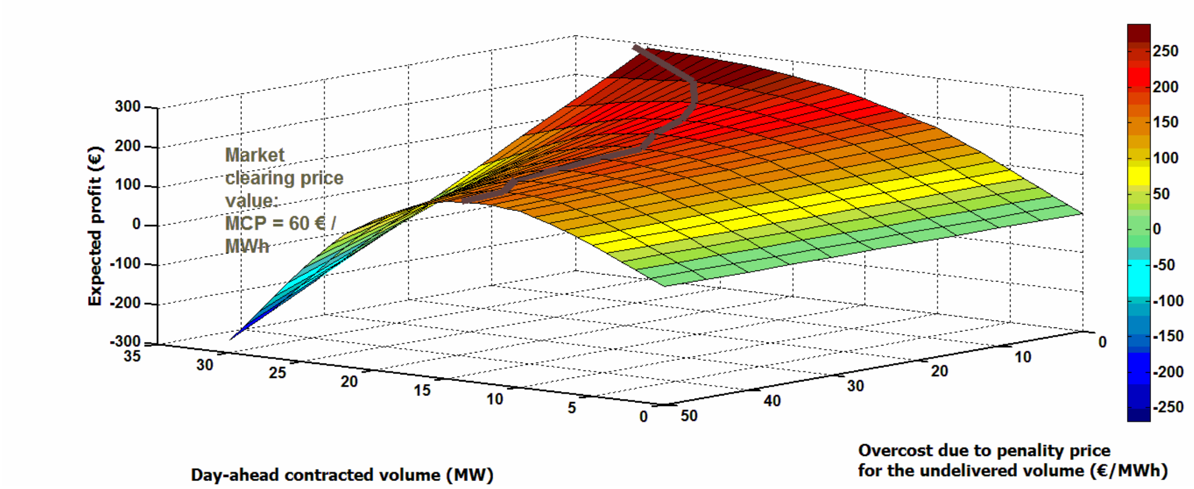

Figure 5. Expected profit of the portfolio as a function of contracted volume and SBP overcharge (case A-1)

Application case

An application case of this work is a VPP demonstration for the European project ALPENERGY, on a rural alpine area. The energy mix of local DERs is presently the following: run-of-river hydraulic, photovoltaic and Diesel peaking plants. Free-access time series of historical French hourly day-ahead and imbalance prices are used [3]. The simulation of commercial VPP is applied on a period of one year, in order to evaluate the long-term commercial performance from energy market real prices. The simulation details and results will not be described in this paper, but several limiting points have been noted.

Firstly, this addition of the new uncertainty parameter leads to the resolution limits of the method which impose an optimization calculation for each scenario: the number of second-class sub-problems will increase exponentially. Secondly, during an annual period, different values of intermittent generation power are expected. In practice, calculation of the aggregated profile has been done for different possible values of the parameters P_E and σ_P. Then, an interpolation of the optimal contracted volume rather than a new update is done for intermediate input values.

Another limitation concerns the extension of the portfolio. As mentioned, the CVPP aggregation problem could be compared with the classical problems of the generation operational planning. As in the simple all-thermal *Economic Dispatch* problem (ED), optimal generation points are calculated independently at each hourly time interval, without dynamic consideration. New generation resources may imply time-related decisions and a larger time horizon (day, week): for example, hydraulic plants with storage capability or CHP units supplying thermal demand.

CONCLUSIONS

This work described a general methodology for the aggregation function of a portfolio of DER into a CVPP, in order to maximize the performance in the day-ahead market. The method is successfully extended to different load-following capability of the dispatchable generators of the CVPP portfolio. However this time-consuming method reaches its limits. An addition of other generation characteristics, particularly time-relative constraints, will impose the use of another class of algorithms, like for example, stochastic dynamic programming.

The portfolio aggregation function can also be extended to the balancing market participation and other ancillary services. As eventual restrictions of generation, due to network constraints, are not taken into account at this level, a step of validation of the scheduling program by a distribution operator could be added, in order to examine eventual consequences on the performance of the portfolio.

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