EVALUATING THE BUSINESS CASE FOR FLEXIBILITIES AS RISK MANAGEMENT IN DIRECT MARKETING OF RENEWABLE ENERGIES

by

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Abstract

Against the background of an increasing competitiveness of distributed energy resources (DER), a stronger market integration - in the form of direct marketing - is politically demanded across the European market areas. Due to the distributed and intermittent character of DER generation, direct marketing introduces new operational risks for DER operators. To ensure profitability, risk management becomes increasingly important. Aggregating DER has proven to be a first step to reduce those risks. In this context, this paper investigates the business case of adding flexible assets (e.g. battery storages, electric vehicles, power-to-heat) for further improving risk management in DER portfolios. For this purpose, a method for evaluating and optimizing a portfolio consisting of DER as well as flexibilities is proposed. The method follows a risk management perspective and considers both a maximization of expected revenues as well as a minimization of risk exposure within its objective. Operational revenues and costs of the evaluated portfolios are determined within a stochastic market-oriented scheduling model, which functions as a sub problem of the portfolio optimization. Additionally, investment costs for all assets are considered. The method is applied to an exemplary DER portfolio and the added value of integrating various flexibility technologies is investigated. The results show an overall positive business case, especially if the flexibilities are able to mitigate volume risks of DER and therefore reduce costs for schedule deviations. At the same time, most flexibility technologies show a decreasing marginal benefit when adding additional capacities. Therefore, dimensioning flexibilities efficiently can have a high impact on their business case.

1. Introduction

To increase the economic efficiency of the distributed energy resources' (DER) targeted deployment, the political demand for stronger market integration has intensified in the European market areas. Recent recommendations and directives drafts of the EU commission include a stepwise reduction of subsidies to incite the transition to purely market based operation [1].

In contrast to subsidy-based operation, there are two challenges associated with the direct marketing of DER. First, current market requirements (e.g. minimum lot size of products) pose a significant entry barrier for individual, small to medium-sized DER. Consequently, established DER marketing concepts envisage a certain level of aggregation. Second, the direct marketing of DER is subject to market risks. These risks are caused by uncertainties related to the forecasting of intermittent generation (volume risk) and spot market prices (price risk). Both risks have an impact on the profitability of direct marketing. While price risks directly influence market revenues, volume risks cause schedule deviations, which have to be compensated by expensive balancing energy. Therefore, to increase profitability of direct marketing and support a purely market based remuneration of DER, risk management strategies must be considered.

Against this background, aggregating DER (e.g. to a virtual power plant) has proven to be an efficient approach to support direct marketing of DER. It enables both overcoming market entry barriers and the use of flexibilities for managing the risks of intermittent generation. Flexible assets such as battery storage systems (BSS) and combined heat and power (CHP) plants are used to react to forecasting errors and compensate schedule deviations. The technical feasibility of this concept as well as the existence of a general business case for exemplary flexibilities have been shown in previous papers, e. g. [2]. However, detailed evaluations of the business case for flexibilities as a tool for risk management in the direct marketing of an aggregator as well as a comparison between different flexibility technologies are missing. As a risk management tool, flexibilities can both increase revenues and minimize risks by moving sales to times with higher prices (compensating price risks) or by compensating schedule deviations (reducing balancing energy costs). On the other side, operational and investment costs of integrating flexibilities into the portfolio have to be considered.

Therefore, this paper proposes a method for evaluating and optimizing an asset portfolio including DER as well as flexibilities. The flexibilities' benefits of both increasing revenues and reducing market risks of DER are evaluated based on a stochastic market-oriented scheduling approach. Hence, the key contributions of this paper are twofold:

1. Development of a comprehensive method for portfolio evaluation and optimization, considering both expected revenues as well as operational risks
2. Assessment and comparison of the business case of various flexibility technologies within a DER portfolio

2. Analysis of Flexibility Options for a DER Portfolio

Integrating flexibility options in direct marketing of a DER portfolio allows for mitigating market risks of intermittent generation. Two general operational strategies for flexibilities can be distinguished:

- Flexibilities can **compensate price risks**, by buffering generation and shifting sales to times with higher forecasted market prices. By increasing sales prices the overall revenue of the portfolio is improved.
- Flexibilities can react to short-term forecasting deviations by storing (increasing consumption) or feeding-in (reducing consumption), which allows **compensating volume risks** of intermittent generation. By improving the schedule adherence of the portfolio, balancing energy costs can be reduced and the overall market efficiency is increased.

These operational strategies require the interconnection of controllable generation, storage systems or flexible loads with the control system of an aggregator (e.g. virtual power plant) via information and communication technology (ICT). The interconnection allows the aggregator to request flexibility from all assets via control signals.

Depending on the technology of flexibility asset, flexibility potential is available in either the positive (feeding-in / reducing consumption) or negative (storing / increasing consumption) direction. The efficient usage of flexibilities by an aggregator requires modelling the assets within a market-oriented scheduling method. The models must comply with the assets' operational restrictions, which can result from two operational requirements [3], [4], [5], [6]:

- **Technical restrictions** describe the technology-specific limits of assets and are determined by the dimensioning and functionality of the asset. Primarily, it has to be determined if and to which extent positive or negative flexible power can be provided. Additionally, storage capacities and power gradients have to be considered.

- **Asset owner requirements** can reduce the assets' flexibility potential for the aggregator beyond the limits of the technical restrictions. Especially requirements ensuring the compliance with comfort conditions related to the asset's utilization - set by the asset owner - have to be taken into account (in particular for flexible loads). Otherwise, owners are likely to withdraw their assets from the aggregators' portfolio.

Aside from operational requirements, flexibility potential can be restricted by adverse financial consequences, e. g. increasing operational costs in case of flexibility requests by the aggregator. Such opportunity costs do not pose hard limits, but rather have to be considered when scheduling the flexibility options within the optimization method [7].

2.1 Distributed Generation

Wind power plants (WPP), photovoltaic (PV) and bio-fueled combined heat-and-power plants (CHP) account for the largest share of renewable energy expansion worldwide [8]. Therefore, these technologies are focused in this paper.

The WPP's and PV's feed-in is mainly influenced by weather conditions leading to an intermittent generation characteristic. On the one hand, weather conditions are highly dependent on the specific location of the generation unit and influence both the overall generation quantity and the forecasting quality. Therefore, the evaluation of intermittent DER requires a location-specific analysis of each relevant unit. On the other hand, operational flexibility of intermittent DER is very limited. Increasing the feed-in above the weather-dependent generation is not possible. Curtailing or turning off the assets completely is technically possible. However, due to negligible variable costs, curtailing causes opportunity costs amounting to the lost market revenues.

CHP plants on the other side are, if the necessary ICT-infrastructure is installed, controllable within their full capacity. Restrictions occur when the CHP-plant is coupled to a heating load and a thermal demand has to be covered. In this case, the CHP has to be treated as a flexible load as well. Additionally, the flexibility is influenced by the assets' thermic and mechanic properties which determine start-up times, maximum power gradients and generation efficiency [9]. If the CHP is not operated at full capacity, opportunity costs result from lower efficiency factors as well as lost market revenues.

2.2 Flexible Loads

Flexible loads comprise all load technologies that possess a time-adjustable consumption. In contrast to storage systems, flexible loads do not have the ability to feed power back into the grid. The provision of positive flexibility is therefore only possible by temporarily curtailing the demand. The flexibility potential of loads increases with the duration, up to which the load can be shifted [5].

Therefore, especially load technologies with an inherent storage have a high flexibility potential. Hence, these technologies can temporally decouple the electricity procurement from the actual consumption. Storage capacities can consist of thermic or electric storages.

- **Thermic storages** are used in heating or cooling appliances (P2H, P2C), e.g. electric storage heaters, heat pumps and air conditioning). Furthermore, they are used in CHP-plants to create flexibility in covering heat demands.
- **Electric storages** are used in electric vehicles (EV). Modern EVs are not equipped with the functionality of feeding power back into the grid (Vehicle-to-Grid / V2G). For future vehicle models, such a functionality is discussed.

The load-shifting potential of flexible loads with an inherent storage is mainly determined by the storage capacity. Additionally, flexible loads are characterized by their primary function of covering a specific load. In case of P2H or P2C units, this function consists of maintaining a certain temperature level, which requires a certain amount of energy. The energy demand varies according to exogenous factors like the outside temperature. In case of electric vehicles, the primary function consists of fulfilling the mobility requirements of the owner. Firstly, this requires a sufficient state-of-charge (SOC) at the beginning of each journey. Secondly, in contrast to the heat demand of P2H units, the mobility requirements do not necessarily exhibit recurring, predictable patterns. Therefore, a certain state-of-charge must be guaranteed at all times to allow for unplanned journeys. Additionally, the non-stationary application causes a time-variability of storage power and capacity, because the EVs are only available for the aggregator when connected to the grid.

Due to the low capacity of single flexible load units and the flexibility limitations caused by mandatory load coverage, the use of single units in the direct marketing of an aggregator is not practical. Therefore, flexible loads can only be integrated as an asset pool. This enables the aggregation of flexible storage capacity and power. For a sufficiently large pool, a statistical availability of non-stationary storages can be assumed.

2.3 Electric Storage Systems

Electric storage systems allow both storing and feeding power into the electricity grid. Besides stationary batteries, electric vehicles can also be used as storage systems. Hereby, the same operational constraints apply as for the use as a flexible load. Especially, the time-variability of the storage capacity and the mobility requirements limit their comparability to full-fledged storage systems. For stationary battery storage systems (e.g. Lithium-Ion, Redox-Flow) these constraints to not apply. Their flexibility is only limited by constraints regarding minimum and maximum power as well as capacity.

Fig. 1 summarizes the flexibility potential and restrictions for the investigated technologies.

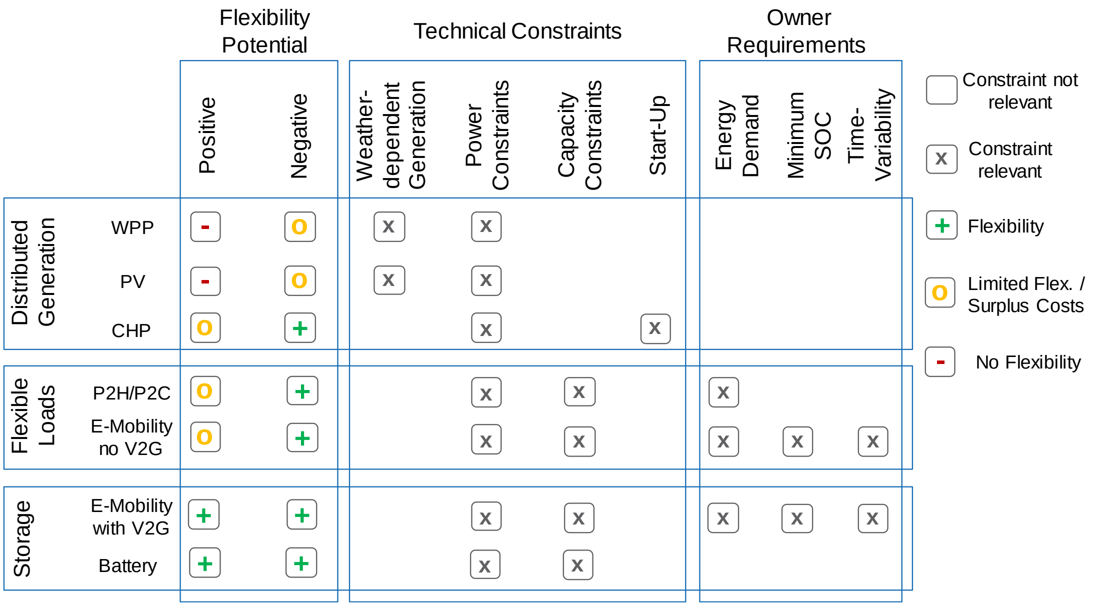


Fig. 1: Classification of the flexibility potential of the analyzed assets

3. Model for Portfolio Evaluation and Optimization

3.1 Overview

The model for portfolio optimization and evaluation proposed in this paper is based on a genetic algorithm including two sub problem stages (cf. Fig. 2). The two sub problems separate the selection of the intermittent DER portfolio (stage 1), i.e. wind power and photovoltaic plants, from the dimensioning of flexibility options (stage 2). The separation arises from the different requirements and challenges in simulating the operation of intermittent DER on the one hand and flexibilities on the other hand.

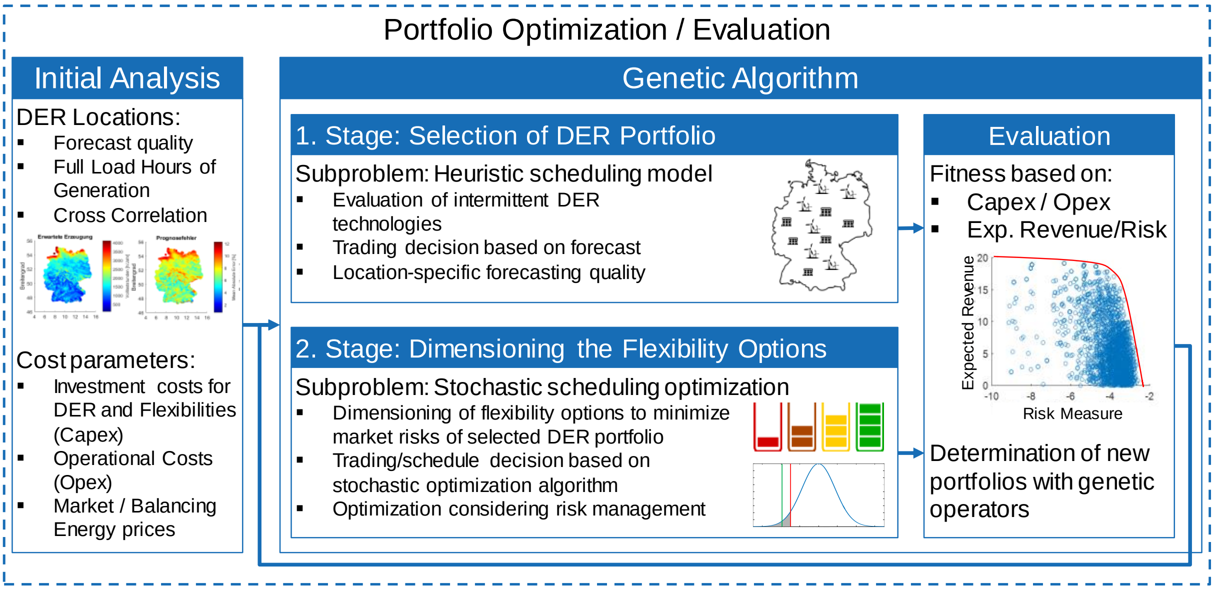


Fig. 2: Overview of the proposed portfolio optimization and evaluation model

The evaluation of intermittent DER requires a location-specific analysis of weather conditions and respective generation characteristics. This leads to a high number of possible asset candidates and therefore to a high degree of complexity in the portfolio optimization. On the other hand, the operational scheduling decision is rather simple for these technologies, as the flexibility of intermittent DER is limited. In particular for the case of positive market prices, curtailing DER can be neglected and the traded amount can be approximated by the forecast. If the actual generation differs from the forecast, schedule deviations in the amount of the difference between forecast and actual generation occur and have to be compensated by purchasing balancing energy.

In contrast, the evaluation of flexibility options exhibits different challenges. In a first approximation, each flexibility technology can be represented by a single aggregated asset. Therefore, the portfolio optimization problem can be reduced to one variable per flexibility technology, which results in low computational complexity. The operational sub problem on the other side must comprise of a complete and disaggregated stochastic scheduling optimization. A mixed integer linear programming (MILP) problem including time-coupling constraints is necessary to appropriately model the technical and owner-induced constraints of the flexibilities. Due to the high computational complexity, this operational sub problem can only be solved for a limited number of portfolios in an adequate time. Hence, it is not feasible for stage 1.

Both sub problems simulate market participation of the asset portfolio over one full year in an hourly time resolution.

3.2 Evaluation

The described model can be used either for portfolio optimization or just as an evaluation model. If it is used for optimization, the model infrastructure of the genetic algorithm (GA) consists of the stages initialization, fitness evaluation and genetic operators for determining new candidate portfolios. The overall GA structure follows the approach presented in [10]. If it is used only for portfolio evaluation, the model allows predefining portfolios as well. In this case, the genetic operators are not used for determining new portfolio candidates and only the predefined portfolios are investigated.

Initialization

Within the initialization stage, the population room is defined, which consists of the solution space of all asset candidates. Each asset candidate is encoded as a discrete variable x_n representing overall installed capacity (e.g. CHP and battery storage system) or the number of integrated pool units (e.g. P2H and EV pools). Upper and lower bounds of each asset variable can be parameterized by the user. Additionally, cost parameters (CAPEX and OPEX) for each asset have to be defined. The model allows for either a random initialization or an initialization of a predefined start population. If random initialization is chosen, various types of portfolios are created:

- Zero Portfolio (no asset candidates are chosen / benchmark case)
- One-Technology Portfolios (only candidates of one technology are chosen)
- Multi-Technology Portfolios (candidates of all available technologies are chosen)

The initialized portfolios constitute the first generation of the GA and are given to the sub problems. They are evaluated with the heuristic scheduling model (stage 1) or the stochastic scheduling optimization model (stage 2), depending on whether flexibilities are integrated in the portfolio.

Fitness Evaluation

After the portfolios have been simulated in the operational sub problems (cf. section 3.3/3.4), their fitness F is defined as return on investment (RoI) and is evaluated based on operational results (OP) from the sub problem as well as capital costs per year (CAPEX) (eq. 3-1). The investment costs are converted into CAPEX with the annuity factor ann_n, which depends on imputed interest r as well as lifespan y of asset n (3-2) – (3-3).

$$F = (OP - CAPEX)/CAPEX \tag{3-1}$$

$$CAPEX = \sum_{n=1}^{N} ann_n \cdot C_n^{inv} \cdot x_n \tag{3-2}$$

$$\text{With: } ann_n = \frac{(1+r)^{n} \cdot n}{(1+r)^{n}-1} \tag{3-3}$$

Operational results consider uncertainty due to market risks and comprise expected revenues and operational costs $E(REV_s - OPEX_s)$ across all scenarios as well as a risk measure quantifying the risk exposure (eq. 3-4). The higher the risk aversion $\beta \in [0,1]$, the more important the risk measure becomes within the overall fitness. The Conditional-Value-at-Risk (CVaR) is chosen as risk measure due to its advantageous properties compared to other risk measures. A more detailed description can be found in [11]. An intuitive explanation of the CVaR can be stated as follows: The further the CVaR is below the expected revenue, the more risky the scheduling decision is. Minimum risk exposure (risk of zero) is reached if CVaR and expected revenue are identical. Hence, the model tries to maximize expected revenue and to bring the CVaR as close as possible to the expected revenue at the same time.

$$OP = (1 - \beta) \cdot E(REV_s - OPEX_s) + \beta \cdot CVaR \tag{3-4}$$

The fitness values are tested against various stopping criteria to determine the convergence behavior towards an optimal solution. Convergence is assumed and the GA is terminated if one of these criteria is fulfilled:

- No changes in best fitness value over the last two generations
- No significant changes (>1%) in the 25% quantile of all individuals over the last two generations
- Maximum number of generation reached (no convergence assumed)

Genetic Operators

If the stopping criteria are not fulfilled, a new portfolio generation is created. This is done by using the genetic operators selection, recombination and mutation [10].

- During the **selection**, portfolios are derived from the prior generation (parent generation) to compose the new child generation. In this model, the tournament selection is used, which chooses portfolios from a tournament of random parent portfolios. The portfolio with the highest fitness value is transferred to the child generation.
- In the **recombination**, the chosen child portfolios are combined by randomly swapping assets. Hence, completely new asset combinations can be found within the solution space.
- During the **mutation**, the variables of individual assets in a child portfolio are changed within their bounds. This allows for slightly expanding or reducing existing portfolios without changing the overall portfolio constellation.

3.3 Stage 1: Selection of DER portfolio

The first stage sub problem is used to select the optimal intermittent DER portfolio (WPP, PV). The selection is based on expected revenue as well as risk caused by schedule deviations due to forecasting errors. The forecasting errors are modelled via stochastic generation scenarios for each investigated DER location. The analysis of DER locations is done based on a database of the German Weather Agency [12], which provides historic weather forecasts and measurement data. The described database allows for an analysis of DER locations regarding:

- generation quantity per year
- forecasting quality and errors
- temporal and regional correlations of forecasting errors

Based on the analysis, the forecasting errors are modelled via auto-regressive moving-average (ARMA) time series models and transformed into discrete stochastic generation scenarios. Additionally, scenarios for market prices are generated based on a price forecast. ARMA models are suited for a wide variety of error distributions and can be parameterized individually for each DER location and the market price. The scenario generation is performed according to the process in [13], [11]. Fig. 3 shows exemplary scenarios generated with this method.

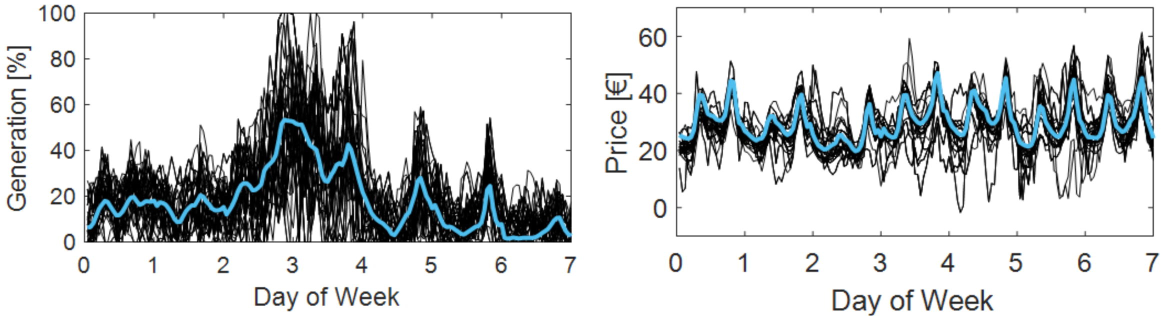


Fig. 3: Exemplary generation scenario family (black) based on forecast (blue) for generation (left) and market prices (right)

Heuristic Scheduling Model

The analyzed DER locations together with the generation scenarios are considered candidates in the portfolio optimization. The portfolio evaluation is done within the following heuristic scheduling model. The heuristic assumes a standard trading decision equaling the generation forecast. The stochastic scenarios represent possible outcomes for actual generation and therefore determine the schedule deviations. All schedule deviations must be compensated by balancing energy.

The operational revenues REV_s of a portfolio are calculated according to equation (3-5). The forecasted generation quantity $P_{t,n}^{FC}$ in time step t is summed up for all portfolio assets $n \in N$ and multiplied with the respective day-ahead market price scenarios $c_{s,t}^{DA}$. If subsidies apply for an asset n, e.g. market premium in Germany, they can be included via $subs_n$ into the revenue.

$$REV_s = \sum_{t=1}^{T} \left(\sum_{n=1}^{N} (c_{s,t}^{DA} + subs_n) \cdot P_{t,n}^{FC} \right) \tag{3-5}$$

Operational costs $OPEX_s$ are scenario dependent and include variable generation costs c_n^{var} as well as balancing energy costs, which are determined by multiplying the balancing energy prices c_t^{BE} with the scenario specific schedule deviations $P_{s,t}^{BE}$ (eq. 3-6). The schedule deviations result from the difference between the scenario generation $P_{s,n,t}^{Act}$ and the forecast $P_{n,t}^{FC}$ (eq. 3-7).

$$OPEX_s = \sum_{t=1}^{T} \left(\sum_{n=1}^{N} (c_n^{var} \cdot P_{t,n}^{FC}) + c_t^{BE} \cdot P_{s,t}^{BE} \right) \tag{3-6}$$

With:
$$P_{s,t}^{BE} = \left| \sum_{n=1}^{N} P_{s,n,t}^{Act} - P_{n,t}^{FC} \right| \tag{3-7}$$

3.4 Stage 2 : Dimensioning the Flexibility Options

After the optimal DER portfolio is determined and evaluated in stage 1, the profitability of adding flexibility options into the portfolio is evaluated in stage 2. The asset data of the DER portfolio together with the scenarios for generation are used as inputs. The scheduling optimization is based on a stochastic mixed integer linear programming algorithm and is shown in Fig. 4. The overall model structure has been proposed in [13]. It is analogous for the portfolio evaluation and not described in more detail in this paper. Instead, this paper focuses on the model expansions necessary for evaluating the economic efficiency of flexibilities, especially the modelling of the different technical and owner-induced constraints.

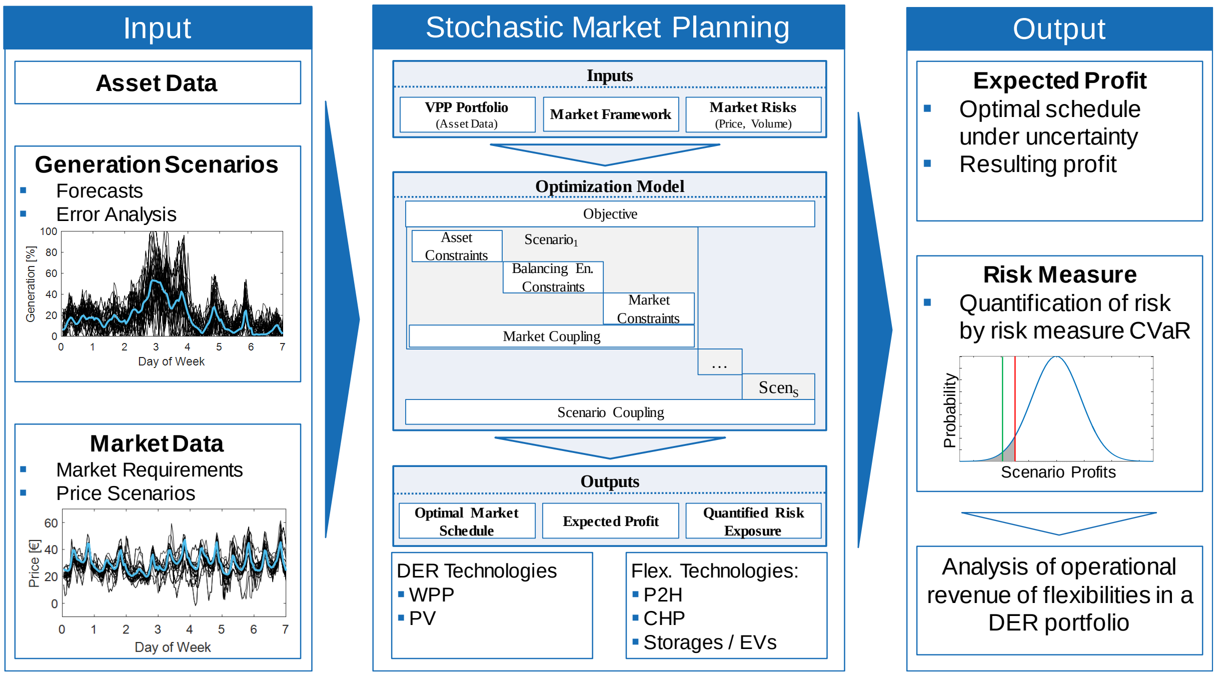


Fig. 4: Overview of the stochastic scheduling optimization method

The algorithm determines the optimal market schedule in a customizable resolution (hourly by default). In general, the model follows a bottom-up approach, meaning all assets are modelled individually. For the intermittent DER, this allows for a detailed modelling of the location-specific generation characteristics and forecasting errors. Within the portfolio optimization method, flexibilities are exempted from the bottom up approach. They are approximated by one representative asset per technology to keep the computational burden acceptable. The different assets are aggregated to one portfolio by coupling constraints. Additional coupling constraints are used to connect the stochastic scenarios and to guarantee an aggregated and scenario-independent portfolio trading schedule. The optimizations' objective is set analogously to stage 1 to keep the results comparable. It aims at maximizing the scenario profits including market revenues as well as operational and balancing energy costs.

The contribution of each flexibility technology to the portfolio is modelled via the power variable $p_{n,t}$ for asset n in time step t. The flexibility contribution is limited by the operational restrictions analyzed in section 2.

Power Constraints

The power provision $p_{n,t}$ is limited by the upper bound P_n^{max} and the lower bound P_n^{min} (eq. 3-8). In general, the upper bound is determined by the installed capacity. The lower bound is usually assumed to be zero, except for bidirectional storages, for which it is set as the maximum feed-in power.

$$P_n^{min} \leq p_{n,t} \leq P_n^{max} \tag{3-8}$$

Start-Up Times

In the operation of CHP plants, additional restrictions for start-up times and generation efficiency have to be considered, which limit the flexible controllability. Start-up times and maximum gradients restrict the change in generation between time steps. For distributed small scale CHP plants these range between a few minutes [9] and can be neglected in a market planning with a temporal resolution of one hour. However, changes in the efficiency factor due to partial load impact the costs of flexibility and have to be considered in market planning. In this model, they are represented by k binary partial load factors b_k^{TL}, which allow modelling a non-linear efficiency factor function. The generated power $p_{n,t}^{CHP}$ results from equations (3-9) – (3-10). The coupling in eq. (3-11) guarantees the selection of exactly one partial load factor. Each partial load factor gets assigned one efficiency factor η_k^{PL}, which determines specific fuel consumption and therefore variable costs within the objective.

$$p_{n,t}^{KWK} = \sum_{k=1}^{K} p_k \cdot b_{k,t}^{TL} \tag{3-9}$$

$$\text{With}: p_k = k \cdot \frac{P_n^{max}}{K}, b_{k,t} \in \{0,1\} \tag{3-10}$$

$$\sum_{k=1}^{K} b_{k,t}^{TL} \leq 1 \tag{3-11}$$

<u>Storage Capacity</u>

The flexibility of assets with an electric or thermic storage is mainly determined by the available storage capacity. The state of charge $SOC_{n,t}$ of asset must not exceed the maximum capacity SOC_n^{max} or go below minimum capacity SOC_n^{min} in any time step t (eq. 3-12)

$$SOC_n^{min} \leq SOC_{n,t} \leq SOC_n^{max} \tag{3-12}$$

The state of charge in any time step $t^* \in [1, T]$ results from the difference between power input $p_{n,t}^{in}$ (storing) and power output $p_{n,t}^{out}$ (feed-in) up to this time step plus the initial state $SOC_{n,0}$. Within this model, power in- and output are defined as electric power, independent of the storage technology. Calculating the state of charge makes a conversion into electric or thermic energy with the respective efficiency factor ($\eta_n^{el}, \eta_n^{th}, \eta_n^{mat}$) necessary (eq. 3-13)

$$SOC_{n,T}^{el,th,mat} = \eta_n^{el,th} \cdot \left(\sum_{t=1}^{T} p_{n,t}^{in} - p_{n,t}^{out} \right) + SOC_{n,0}^{el,th} \tag{3-13}$$

Power in- and output result from power provision to the markets $p_{n,t}$ or, in case of flexible loads, from load coverage $p_{n,t}^{load}$ (eq. 3-14).

$$p_{n,t}^{out} - p_{n,t}^{in} = p_{n,t} + p_{n,t}^{load} \tag{3-14}$$

Furthermore, for bidirectional storages, a unique power direction for each time step must be ensured to prevent inconsistent storage behavior within the planning. Therefore, the binary variables $b_{n,t}^{in}$ and $b_{n,t}^{out}$ are added to the model, which determine the power direction in time step t. Simultaneous power in- and output is prevented by applying the big-M method in equation (3-15) – (3-17).

$$p_{n,t}^{out} - M \cdot b_{n,t}^{out} \leq 0 \tag{3-15}$$

$$p_{n,t}^{in} - M \cdot b_{n,t}^{in} \leq 0 \tag{3-16}$$

$$b_{n,t}^{out} + b_{n,t}^{in} \leq 1, \text{with } b_{n,t}^{in}, b_{n,t}^{out} \in \{0,1\} \tag{3-17}$$

<u>Load Coverage</u>

Power output for load coverage $p_{n,t}^{load}$ is determined by a specific exogenous load profile of each asset. As analyzed in section 2, using single flexible loads in direct marketing is not practical. In this model, flexible loads are therefore controlled as aggregated pools. The pools' demand results from the sum of electric or thermic demands $d_{i,t}$ of all pool units i. For power-to-heat units typical heat demand profiles are used. The conversion in electric power output is done via the thermic efficiency factor η_i^{th}. For electric vehicles, the load profiles are modelled from statistical driving behaviors [14]. The pool demand is determined according to eq. (3-18).

$$p_{n,t}^{load} = \begin{cases} \sum_{i=1}^{I} \frac{1}{\eta_i^{th}} d_{i,t}^{th} & for\ thermic\ loads \\ \sum_{i=1}^{I} d_{i,t}^{el} & for\ electric\ loads \end{cases} \tag{3-18}$$

Minimal SOC & Time-Variability

Electric vehicles represent an exception among flexible loads because the mobility requirements cause a non-stationarity of the storage capacity. This constraint leads to additional challenges for the assets' scheduling, which must guarantee a sufficient SOC before each journey for the owner as well as an accurate determination of the time-variable flexibility potential of storage capacity and power for the aggregator. For an EV pool, this means that storage capacity and power depend on the number of vehicles connected to the grid at a specific time step t. This is represented by the state variable $s_{i,t}$ for vehicle i. Equations (3-19) – (3-21) show the calculations for variable storage constraints of the EV pool.

$$-P_{n,t}^{min} = P_{n,t}^{max} = \sum_{i=1}^{I} s_{i,t} \cdot P_i \tag{3-19}$$

$$SOC_{n,t}^{max} = \sum_{i=1}^{I} s_{i,t} \cdot SOC_i^{max} \tag{3-20}$$

$$\text{Mit: } s_{i,t} = \begin{cases} 1 & vehicle\ i\ connected\ to\ grid\ in\ time\ step\ t \\ 0 & vehicle\ i\ not\ connected\ to\ grid\ in\ time\ step\ t \end{cases} \tag{3-21}$$

Furthermore, the owner-induced requirement of a sufficient SOC at the beginning of each journey causes an additional constraint for the lower bound of the pools' storage capacity. In this model, a conservative estimate is done by requiring a fully charged battery for each journey. In each time step a lower bound $SOC_{n,t}^{min}$ is determined by the number of departing vehicles veh_t^{leave} multiplied with their maximum storage capacity SOC_i^{max} (eq. 3-22).

$$SOC_{n,t}^{min} = veh_t^{leave} \cdot SOC_i^{max} \tag{3-22}$$

Overall, the available time-variable flexibility is shown exemplary as a hatched blue area in Fig. 5.

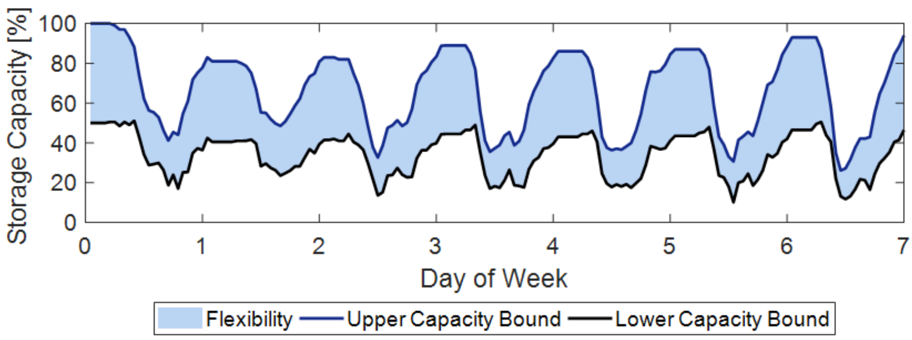


Fig. 5: Exemplary time-variable flexibility of an EV pool

4. Introduction to the Study Case

The proposed method is applied to an exemplary study case. As the focus of this paper lays on the evaluation of flexibilities, the selection of a DER portfolio is not part of the investigation but rather predefined. For this purpose, stage 2 of the genetic algorithms' sub problem is used for evaluating the optimal addition of flexibilities to the predefined DER portfolio.

DER Portfolio

We assume a DER portfolio consisting only of intermittent WPP and PV units, which allows investigating the influence of adding flexibilities. The portfolio includes 7 WPP and 5 PV units, which are regionally distributed and show different levels of forecasting uncertainty. The hourly forecasting error varies between 5% - 11% (normalized to installed power). Each asset is assumed to have a capacity of 2.3 MW, which amounts to a total of 27.6 MW of intermittent generation.

Flexibility Options

The flexibility candidates for the portfolio are shown in Table 1. For CHP and battery storage systems, the capacity is assumed to be aggregated in one asset and can be dimensioned according to certain capacity steps up to a maximum capacity. The EV and P2H pools consist of a maximum of 100 units, which have a fixed maximum capacity per unit. Within the optimization, the number of units that are integrated into the pool are determined.

Table 1: Flexibility candidates for the exemplary DER portfolio

Technology	**Max. Capacity [MW/unit]**	**Max. Unit**	**Capacity/Unit Steps**
CHP	10	1	2.5 MW
Battery Storage	10	1	1.25 MW
EV pool	0.011	100	25 units
P2H pool	0.015	100	25 units

The cost parameters and life times assumed for each flexibility candidate are shown in Table 2. Cost parameters are divided in investment (CAPEX), fixed and variable operational costs (OPEX). For CHP and battery storage systems, the aggregator is assumed to be the asset owner. Therefore, CAPEX include all investment costs. For EV and P2H pools, the aggregator only contracts the assets and integrates them into the portfolio. Therefore, CAPEX only comprise investment in ICT-infrastructure.

Table 2: Cost parameters for flexibility candidates based on [15], [16], [17]

Technology	**CAPEX**	**Fixed OPEX**	**Variable OPEX**	**Life Time [y]**
CHP	2.7 Mio. €/MW	0.04 * CAPEX	30 €/MWh_{th}	30
Battery Storage	450 k. €/MW	0.01 * CAPEX	-	15
EV pool	450 €/unit	30 €/unit	-	5
P2H pool	450 €/unit	30 €/unit	-	5

Market Prices

The day-ahead market (DA) prices assumed are the 2016 actual market prices, which are shown in Fig. 6. For studying the business case in risk management, the balancing energy costs play a major role. Due to their highly stochastic behavior, forecasting BE prices is not possible. Instead, a certain spread between DA and BE prices is assumed based on historic price data.

The spread results from the calculation rules established by regulation and guarantees an incentive to minimize balancing energy demands [18].

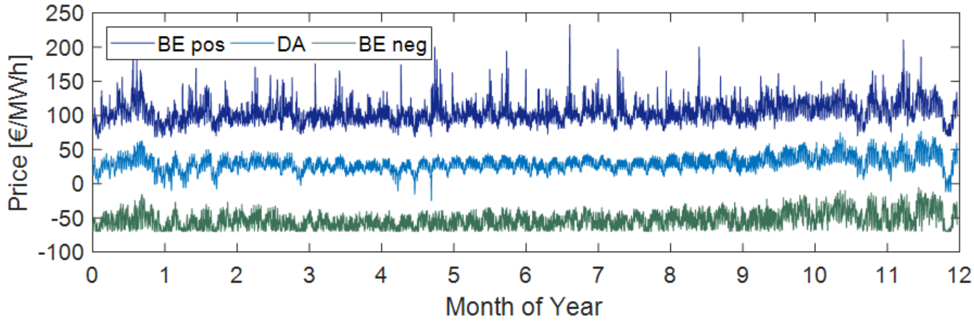


Fig. 6: Day-Ahead market prices and balancing energy costs (BE) assumed in the study case

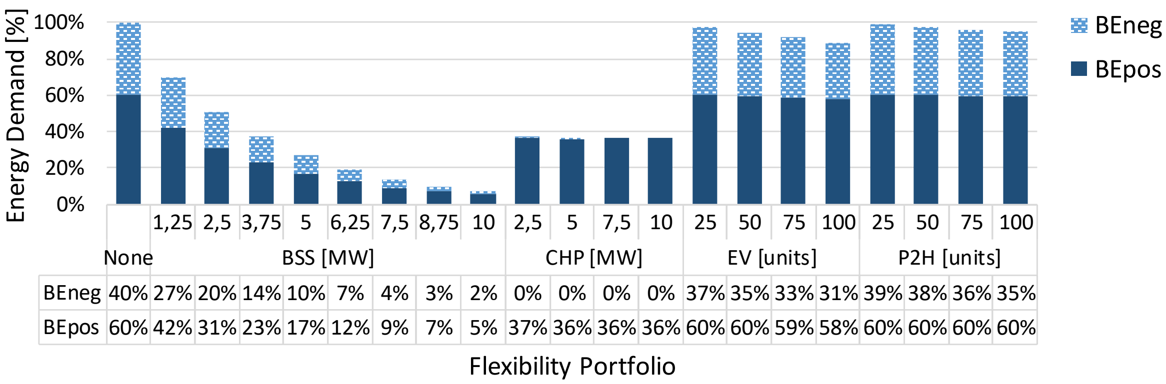
5. Evaluation Results

The portfolio evaluation and optimization method is applied to the exemplary study case. The results are structured as follows.

- The **operational revenue** regarding the mitigation of risks is evaluated separately for each flexibility candidate. The portfolio optimization model is used with the predefined portfolios each consisting of one flexibility candidate. The stage 2 sub problem (stochastic scheduling optimization model) is used and investment costs are neglected in this investigation. Each flexibility candidate's contribution to the DER portfolio's performance is assessed using the following criteria:
  - Balancing Energy Demand
  - Expected Operational Revenue
  - Conditional Value at Risk
- The **return on investment** is evaluated using the portfolio optimization model as well, whereby the cost parameters shown in Table 2 are considered. This evaluation allows assessing the business case of each flexibility option based on the following criteria:
  - Expected return on investment
  - Conditional Value at Risk
- The **optimal flexibility portfolio** for the exemplary study case is determined with the GA and the optimal combination of flexibilities is chosen. Within the optimization, the fixed capacity/unit steps from Table 1 are not taken into account. Instead any integer solution up to the maximum capacity / number of units can be selected. For the risk aversion, a factor $\beta = 0.5$ is chosen in this investigation.

5.1 Operational Revenue

The balancing energy demand correlates with the schedule deviations of the asset portfolio and is highly dependent from the amount of volume risk present during the market participation. Fig. 7 shows the impact of separately adding each flexibility candidate on positive and negative balancing energy demands of the portfolio. The DER portfolio without flexibilities is used as benchmark ("None").



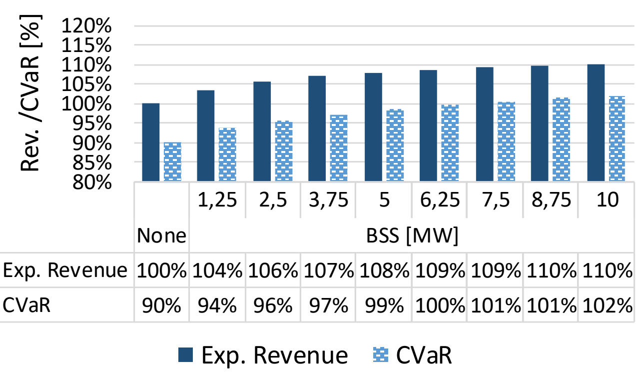
	None	BSS [MW] 1,25	2,5	3,75	5	6,25	7,5	8,75	10	CHP [MW] 2,5	5	7,5	10	EV [units] 25	50	75	100	P2H [units] 25	50	75	100
BEneg	40%	27%	20%	14%	10%	7%	4%	3%	2%	0%	0%	0%	0%	37%	35%	33%	31%	39%	38%	36%	35%
BEpos	60%	42%	31%	23%	17%	12%	9%	7%	5%	37%	36%	36%	36%	60%	60%	59%	58%	60%	60%	60%	60%

Fig. 7: Influence of the flexibility candidates on balancing energy demand

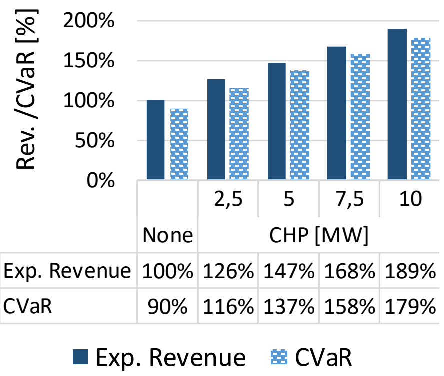
The results show a reduction of balancing energy demands for all flexibility candidates but the respective extent significantly differs:

- Adding additional **Battery Storage System (BSS)** capacities continuously reduces both positive and negative BE demands. However, the marginal benefit declines with increasing storage capacity. Hence, a 50%-point reduction can already be achieved with only 2.5 MW capacity for the exemplary study case. Increasing the capacity up to 10 MW allows for a reduction below 10%-points. This shows the high flexibility potential of battery storage systems (cf. section 2).
- Adding a **Combined-Heat-and-Power plant (CHP)** enables compensating all negative balancing energy demands. Positive BE on the other side is not reduced below 35%-points. The BE demand does not decline with increasing the CHP capacity above 2.5 MW. This result confirms the analysis in section 2 and is caused by the opportunity costs of operating the CHP below full capacity. For providing positive balancing energy, the CHP would have to operate below full capacity permanently to allow for increasing the generation if positive balancing energy is needed. This would significantly reduce full load hours and market revenues. Providing negative balancing energy on the other hand only means temporarily curtailing the CHP for the period in which negative BE is needed. Due to having no storage capacity restrictions, 2.5 MW suffice for compensating all negative BE demands.
- Integrating **EV and P2H pools** into the portfolio reduces negative BE demands. Positive balancing energy is only slightly affected by the EV pool (2%-points). Compared to the BSS, the results show a lower flexibility potential for flexible loads. Firstly, this can be explained with the lower installed capacity (maximum of 1.1 MW for EV and 1.5 MW for P2H) in this study case. Secondly, it is caused by the load requirements.

The overall impact on operational revenue and risk is shown in Fig. 8 – Fig. 9. In each graph, the DER portfolio without flexibilities is used as benchmark (“None”).



	None	BSS [MW] 1,25	2,5	3,75	5	6,25	7,5	8,75	10
Exp. Revenue	100%	104%	106%	107%	108%	109%	109%	110%	110%
CVaR	90%	94%	96%	97%	99%	100%	101%	101%	102%



	None	CHP [MW] 2,5	5	7,5	10
Exp. Revenue	100%	126%	147%	168%	189%
CVaR	90%	116%	137%	158%	179%

Fig. 8: Influence of BSS (left) and CHP (right) on operational revenue and CVaR

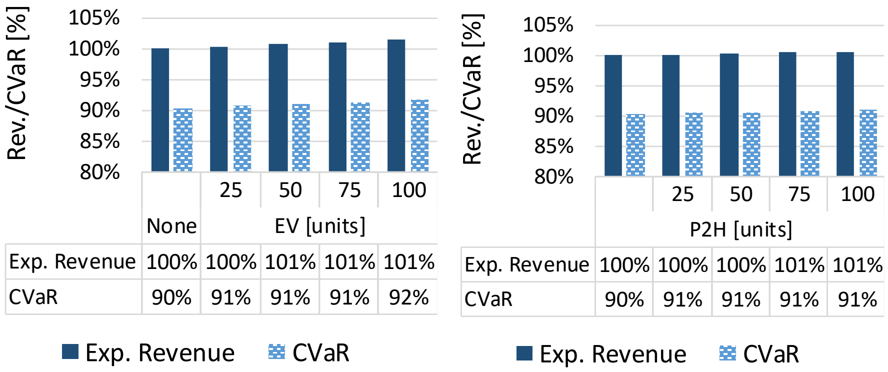


Fig. 9: Influence of EV (left) and P2H (right) on operational revenue and CVaR

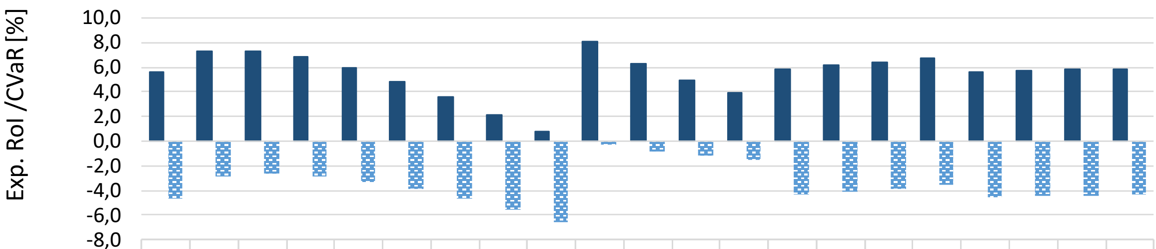
The operational revenues mainly reflect the results regarding balancing energy demands, with all technologies having a positive effect on revenues and on the risk measure CVaR. The CHPs' results differ significantly from the other flexibility technologies. Due to the CHP being not mainly a flexibility but a generation unit, it strongly increases portfolio revenues. Operational risk on the other side, is not reduced which can be seen in the difference between expected revenue and CVaR remaining 10%-points. In case of the BSS and EV pool this difference is reduced by 2%-points and 1%-point, respectively.

5.2 Return on Investment

The return on investment (RoI) including operational revenues as well as operational and investment costs is shown in Fig. 10. The benchmark without flexibilities shows a positive RoI of about 5.6% but a CVaR of -4.6%, which emphasizes the impact of risks on the profitability of DER. Integrating the various flexibility options influences the return in different ways:

- The **BSS** shows a positive business case for storage capacities up to 5 MW with an increasing expected RoI up to 7.3%. The optimal storage capacity regarding expected RoI amounts to 2.5 MW. For larger storages, the RoI declines due to the marginal benefit decrease shown in Fig. 7.
- The benefit of including a **CHP** plant highly depends on the installed capacity. For this exemplary portfolio, including a 2.5 MW plant strongly increases the RoI, but the benefit drops for higher capacities and even falls below the benchmark. This correlates with the influence of the CHP on balancing energy demand. Whereas the first 2.5 MW significantly reduce BE demands, higher installed capacities are only used for trading at the day-ahead market and do not further reduce balancing energy. Here, the market revenues of the CHP plant do not outweigh the high investment and operational costs.
- Integrating **EV and P2H pools** only has a slight operational benefit compared to the BSS and CHP (cf. Fig. 8 – Fig. 9). On the other side, investment costs for integrating the pool units via ICT-infrastructure are much lower than investment in battery storage and CHP. This results in a positive effect on the RoI, especially for the EV pool, which increases the RoI about 1.1%-point The P2H pool only has a small impact of 0.3%-points.

On the one hand, the results show a mainly positive business case for integrating flexibilities in the study case. On the other hand, wrong dimensioning of flexibility assets can negatively affect the return on investment, due to decreasing marginal benefits.



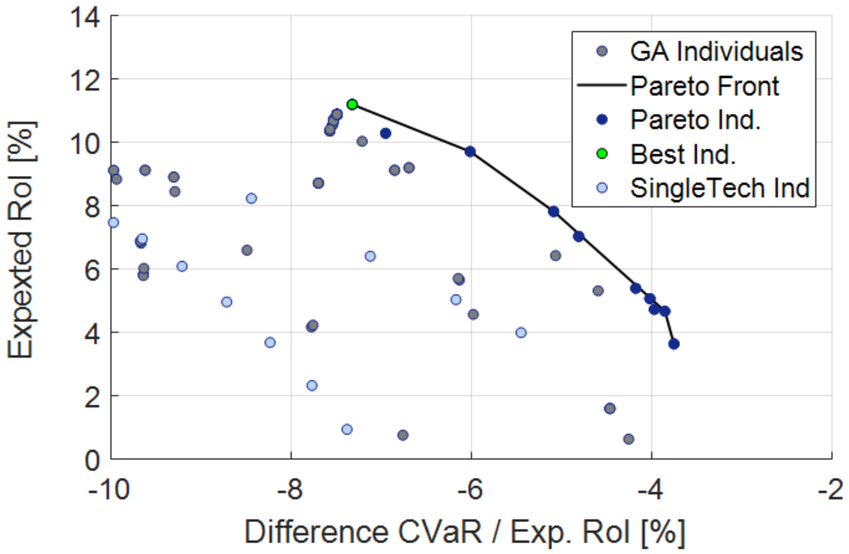
	None	BSS [MW] 1,25	2,5	3,75	5	6,25	7,5	8,75	10	CHP [MW] 2,5	5	7,5	10	EV [units] 25	50	75	100	P2H [units] 25	50	75	100
Exp. RoI	5,6	7,3	7,3	6,8	6,0	4,8	3,5	2,2	0,8	8,1	6,3	5,0	3,9	5,9	6,1	6,4	6,7	5,7	5,7	5,8	5,9
CVaR RoI	-4,6	-2,9	-2,6	-2,8	-3,3	-3,9	-4,7	-5,6	-6,6	-0,3	-0,8	-1,2	-1,5	-4,3	-4,1	-3,8	-3,6	-4,5	-4,5	-4,4	-4,3

■ Exp. RoI ▩ CVaR RoI

Fig. 10: Expected Return on Investment (RoI) and CVaR for all flexibility candidates

5.3 Optimal Flexibility Portfolio

The results of the GA are shown in Fig. 11. Each individual is described by the expected RoI as well as its difference between expected RoI and CVaR. Pareto individuals, which are not dominated by any other individual are shown in dark blue and constitute the pareto front. As a comparison, the single-technology solutions from section 5.2 are shown in light blue. The GA individual exhibiting the best fitness value ($RoI = 11.3\%, CVaR = 3.9\%$) is shown in green. It consists of a 1 MW CHP as well as EV and P2H pools with 100 units each. Due to the combination of various flexibilities within the portfolio, the expected RoI can be increased by 3%-points compared to the single-technology portfolios in Fig. 10.



Best individual

Tech.	**Capacity/ units**
CHP	1 MW
Battery Storage	0 MW
EV pool	100 units
P2H pool	100 units

Fig. 11: Expected Return on Investment (RoI) and difference to CVaR for all individuals of the GA

6. Discussion and Conclusion

In this paper, the business case of flexibilities as a measure for risk management in an asset portfolio consisting of intermittent generation has been investigated. The perspective of an aggregator of DER has been assumed, who is confronted with volume and price risks in direct marketing. For the investigation, a method for optimizing portfolios consisting of DER and flexibilities has been presented and applied to an exemplary study case. Various flexibility technologies have been analyzed regarding their flexibility potential and modelled accordingly within the optimization method. Results have been presented that show the impact of these flexibilities on operational scheduling as well as the overall business case including operational and investment costs. Regarding operational scheduling, all flexibilities achieve a reduction of balancing energy demands, which occur in case of schedule deviations due to volume risks. The extent of reduction differs amongst flexibility technologies and matches the analysis of flexibility technologies performed in this paper. Additionally, a declining marginal benefit of adding flexibility capacity can be identified. When investment costs are considered, a mainly positive business case for integrating flexibilities is shown in this study case, but efficient dimensioning for the specific DER portfolio is crucial. The business case highly depends on assumed cost parameters for integrating the flexibilities as well as cost parameters for balancing energy. Due to investment costs being expected to fall in future, the business case can be expected to improve

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