Economic study of the participation of multiple energy resources in grid services markets *

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Abstract

This paper presents a method to analyze the technical and economic potential of combining different types of resources to provide grid services, with a particular focus on battery systems. The paper proposes a modelling paradigm where resources are described with few key operational parameters and describes a control architecture to co-operate the combination of resources to offer fast grid services, taking as an example the provision of secondary frequency control in the Swiss market. A sensitivity analysis is reported that highlights the ability of the combination of energy resources to provide grid services as a function of their technical characteristics.

1 Introduction

Power grids are undergoing massive changes to reach ambitious targets in terms of reduced carbon dioxide emissions, higher energy efficiency, economic competitiveness and increased security of supply. The increasing share of intermittent renewable energy sources connected to the grid challenges the current power grid stabilization paradigms. Renewable energy production is less predictable and controllable than traditional generation from fuel-based power plants and hydropower units and introduces fluctuations and uncertainty on the generation side which contribute to destabilize the network. In addition, intermittent renewable energy are connected through power inverters which do not provide inertia to the grid in the same way the rotating mass of synchronous generators of traditional power plants do. The increasing need for reserve power, which is now mostly provided by hydro-units and fast-ramping generation resources, has brought attention to the provision of regulation services by demand-side resources [Callaway and Hiskens, 2011] and electric storage resources. The potential of demand side resources has

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recently been identified by authorities in the USA and Europe. For example, the Pennsylvania-Maryland interconnection (PJM), has incentivized the participation of new resources in ancillary services by adapting their participation rules [Zhao et al., 2013]. Regulation services to the grid require accurate and fast control, therefore, they usually take the form of direct control under the form of power production/consumption tracking [Callaway and Hiskens, 2011], [Rebours et al., 2007].

Numerous types of loads or pools of loads have been identified as suitable for providing regulation services, including thermally controllable loads [Hao et al., 2015], interruptible industrial and domestic loads [Douglass et al., 2013], and plug-in hybrid electric vehicles [Andersson et al., 2010]. [Oldewurtel et al., 2013] proposes a framework to study which resources are most suitable for each type of service.

In particular, following the maturation of battery products and steady declines in battery pack prices [IRENA, 2017], electric storage have been evidenced as a credible technical alternative to power plants in numerous situations, in particular grid regulation services provision and renewable integration [Divya and Østergaard, 2009, Oudalov et al., 2007]. The next step consists of looking at economic viability. Existing works in the literature have looked at specific types of resources. In our previous work [Qureshi et al., 2016], the economic implications of utilizing buildings systems for grid support services in the Swiss market were studied in detail. It concluded that buildings participating in the Swiss AS market can reduce on average their operational costs between 8 and 35%, depending on the availability of thermal storage and the opportunity to place trades on the intraday market. The analysis by Lazard [2016] offers a total cost and revenue analysis for different storage technologies on different markets. It identifies possible returns of 13% for investment in storage participating in PJM's frequency regulation market. Megel et al. [2013] propose two new methods to use batteries for frequency control and computes return on investment for the strategies proposed based on some investment cost measure.

While most available studies look at the value of storage alone, there is significant economic value in combining storage systems with other resources and providing flexibility services in coordination. The reason for this is that the main limiting factor of investment in batteries is the price of storage capacity. Due to this, services that require energy intensive actions cannot be provided by batteries alone in an economically beneficial fashion. Combining the battery with other types of resources allows one to direct power intensive tasks to the battery and transfer energy intensive tasks out to the other resources. In this work, we consider the case where the battery is operated in combination with another system whose characteristics are complementary to the ones of the battery in the following sense:

- It is capable of supporting energy intensive profiles, that is it has a large storage capacity. Note that this storage capacity can be "virtual" since this system may not be a storage system per se, but could be a power producing plant that can shift its power operating point up and/or down. This grants the system a practically infinite storage capacity, possibly at the expense of loss-of-opportunity cost of operating away from an otherwise economically optimal operating point.

- It may not be able to perform power-intensive tasks due to technical limitations such as delays in response, power output ramp rate limitations, or noisy output.

We consider the coordination of the system with: i) a physical system that we will call "virtual storage" characterized by physical constraints, which can be used as a proxy for demand response elements or different types of power-generating assets, such as thermal or hydro power plants; and ii) an energy selling and buying market mechanism that is characterized by regulatory rather than physical constraints.

We present here a method to evaluate the economic potential of batteries for grid services which is applied to the case study looking at the provision of secondary frequency control in the Swiss energy market, based on real historical data of the service.

Since we aim at evaluating the combination of a storage system with different types of resources, we have chosen to model the virtual storage based on a few key physical characteristics. The key metric of comparison chosen is the total amount of flexible power that can be provided by the system over its expected lifetime. With this metric, we can directly compare the impact of the physical characteristics of the resource on the level of service that can be provided. However, from an economical point of view, a financial comparison is required. Section 5 proposes methods to draw conclusions regarding best investment strategies.

In this paper the coordination of the battery and the "virtual storage" is considered and the following elements are detailed:

- The control architecture and design is presented (MPC).
- A sensitivity analysis of the influence of the key physical characteristics of the system on its ability to provide the flexibility service is reported.

2 Method of investigation

We aim to evaluate the economic advantage of combining batteries with another flexible resource for fast regulation services. While we present a specific case study that looks at the combination of a virtual storage and a battery for provision of secondary frequency control, this method can easily be extended to other cases.

Our goal is to determine for a given virtual storage characterized by a particular set of physical limitations the best possible investment in a combination of battery and virtual storage in order to provide grid services. The strategy used is sketched in Figure 2.

In order to evaluate a particular combination of resources, we simulate the operation of the full system providing several levels of grids services. The technical and economic performance of the system across this range and the best economic performance achievable are identified. By exploring

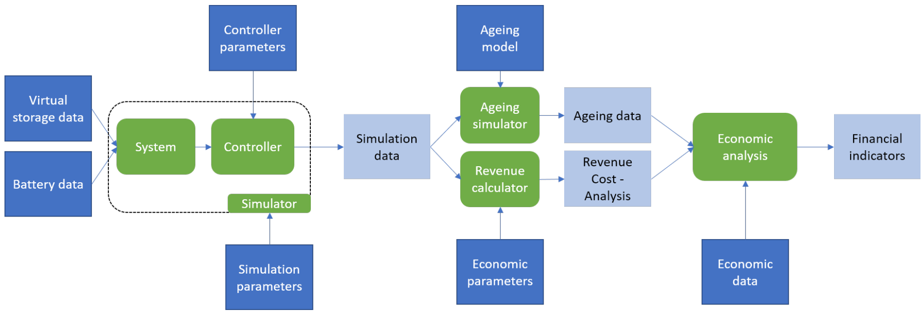

Figure 1: Simulation flow

different respective levels of battery to virtual storage relative investment, the best investment is finally identified.

Figure 2 summarizes the component that are involved in the simulation and the computation of the financial indicators.

The simulator of the system takes as inputs: the system data, the simulation parameters, and the controller parameters; and outputs the simulation data. The simulation data is in turn used to compute the resulting battery aging and determine yearly extrapolated revenues and costs related to the operation of the system in the tested configuration. Finally, an economic analysis routine evaluates the financial indicators for the project looking at the investment in the battery.

Sections 3 provide the details of the technical aspects of the simulation including the simulator, the models used, the controller chosen and the ageing models considered while Section 4 details the revenue, cost computation and the financial investment analysis method.

3 Modeling and simulation

3.1 Systems

We consider the combination of two systems:

- a virtual storage, whose operating capabilities are abstracted out and summarized by three key indicators:
  - Sampling rate: That's the frequency at which the system can be controlled
  - Maximum power rating: The maximum power that the system can generate:
  - Maximum ramp rate: the maximum rate of change of the output.
- An electric storage system, characterized by:
  - Maximum power rating (which is assumed to be symmetric)
  - Maximum storage level.

In addition, the opportunity to trade energy on real-time energy markets is considered. Following the regulations of the European continuous energy markets, it is assumed that energy can be traded on pre-determined periods of time, with a lead time (or gate closure) prior to delivery.

3.2 Modeling

- Battery system described by power rating limitation and state-of-charge constraints. The power injection to the battery is denoted by P_b and the state of charge by s_b. Ye use a load convention so that $P_b > 0$ corresponds to a net charging of the battery. The following constraints hold:

$$\begin{aligned} \underline{P}_b \leq P_b \leq \bar{P}_b \\ s_{\min} \leq s_b \leq s_{\max} \end{aligned} \tag{1}$$

  The dynamics of the battery are characterized by the following equations:

$$s_b^+ = s_b + f(P_b) \tag{2}$$

  where f is a nonlinear function of the charging power that captures the roundtrip efficiency loss of the battery:

$$f(P_b) = \eta_{\text{char}} \max(P_b, 0) + \eta_{\text{disc}} \min(P_b, 0) \tag{3}$$

  and η_{char} the charging efficiency and η_{disc} the discharging efficiency of the battery.

- A "virtual" storage system, whose power injection is denoted P_s (also using load convention). It is characterized by power output limits and ramp output constraints:

$$\begin{aligned} \underline{P}_s \leq P_s \leq \bar{P}_s \\ \underline{\delta}_s \leq \delta P_s \leq \bar{\delta}_s \end{aligned} \tag{4}$$

  where δP_s is the difference of power output between two consecutive time steps. In addition, the sampling time of the system as the frequency at which the power input to this resource can be changed is denoted by T_b and measured in minutes.

- The possibility to trade energy is modeled as a third system with no dynamics, a slow sampling time and a delay which captures the limitations of the gate closure time. We denote by P_m the traded power and $u_m^{t-\delta_m}$ the trade placed at time $t-\delta_m$ for delivery at time t.

$$P_m^t = u_m^{t-\delta_m} \tag{5}$$

  where we still use a load convention so that $P_m > 0$ corresponds to a net purchase of power. δ_m is denoted the gate closure delay.

The models above are simplifications of real systems and market mechanisms that allow one to concentrate the information in few key parameters so that meaningful conclusions can be drawn while disregarding minor details.

We discuss below the consistency of the models with respect to reality.

The model of energy trading is inspired from the setup of most energy trading exchanges. We assume that energy can be traded in periods of 15 minutes with a gate closure before delivery, conforming to the EPEX SPOT market rules: gate closing time is variable depending on the market and is one of the parameters that this study is investigating. It is assumed that trades can be concluded at gate closure which assumes a price taking position and enough liquidity in the market. Liquidity has been steadily increasing in European intraday markets, so the question is one of price, and is discussed in the next section. Note that a longer delay for intraday trades can be used as a proxy to capture the risk of low liquidity in the market.

3.3 Service provided

In this case study, we study the provision of secondary frequency control in Switzerland. Secondary frequency control contributes to the restoration of the frequency to the nominal 50 Hz operation of the power grid. Following the rules of secondary frequency control, we assume the service provision consists of tracking a reference power request.

Upon reception of the tracking request denoted a^t at time t, the total power consumption of the system minus the energy traded is to be made as close to zero as possible. We denote by e^t the tracking error at time t.

$$e^t = P_b^t + P_s^t + P_m^t - a^t \tag{6}$$

We assume that a^t is unknown a priori, although at least one forecast is available for the future values of a.

In this work we provide a detailed analysis of provision of SFC, but the same framework can be used to look at any grid service that consists of tracking an a priori unknown power request. This includes primary, secondary and tertiary frequency control, renewable firming, etc.

3.4 Control method

The coordination between the operation of the battery, the virtual storage and the energy market is discussed in this section. We assume that the primary goal of the controller is to maintain the tracking error as close to zero as possible at all times considering the operating constraints of the system.

At any point in time, we ideally would solve the following optimal control problem:

$$\begin{array}{ll}
\underset{\mathbf{P}_b,\mathbf{u}_m,\mathbf{P}_s}{\text{minimize}} & \mathbb{E}_{\mathbf{a}}\left[\rho(\mathbf{e})\right] \\
\text{s.t.} & \underline{P}_b \leq \mathbf{P}_b \leq \bar{P}_b \\
 & s_{\min} \leq \mathbf{s}_b \leq s_{\max} \\
 & s_b^{t+1} = s_b^t + f(P_b)\, \forall t = 0,\dots,\infty \\
 & \underline{P}_s \leq \mathbf{P}_s \leq \bar{P}_s \\
 & \underline{\delta}_s \leq \delta\mathbf{P}_s \leq \bar{\delta}_s \\
 & P_m^t = u_m^{t-\delta_m}\, \forall t = 0,\dots,\infty \\
 & \mathbf{e} = \mathbf{P}_b + \mathbf{P}_s + \mathbf{P}_m - \mathbf{a}
\end{array} \tag{7}$$

where ρ is a loss function measuring the cost of tracking errors, s_0, P_s^{-1} (required to enforce the ramp limit) are given and $(P_m^0, \ldots, P_m^{\delta_m - 1})$ are given from the solutions of previous iterations of the problem. Note that we assume here for simplicity of notation that the sampling time of the battery, the virtual storage and the trading are identical. If this is not the case, this problem should be solved sampled with the fastest sampling time and appropriate adaptations made.

In reality the true probability generating a is unknown and only historical data is available. We proceed to the following simplifications to approximate the above controller:

- An MPC strategy is used. We define a horizon N and solve the problem in a rolling horizon fashion.
- We introduce a terminal cost in order to capture the tail of the cost. Since no reliable prediction for a is available beyond two hours, we use as a terminal cost the deviation of the state of charge of the battery from a reference state of charge s_{ref}. Since the signal is statistically centered around 0, we choose $s_{\text{ref}} = \frac{s_{\max}+s_{\min}}{2}$. A similar approach is employed by Megel et al. [2017] where a well-tuned cost on state of charge deviation is used in place of a stochastic optimization framework.
- Instead of solving a stochastic problem, we solve the problem for a nominal forecast of the AGC $\hat{\mathbf{a}}$.
- We use a linear approximation of the battery dynamics by neglecting the nonlinear efficiencies. We refer to Megel et al. [2017] for possible solution methods to solve the same problem while considering nonlinear efficiencies.

The controller therefore solves the following problem

$$
\begin{array}{ll}
\underset{\mathbf{P}_b, \mathbf{u}_m, \mathbf{P}_s}{\text{minimize}} & \rho(\mathbf{e}) + \rho_f(s_N) \\
\text{s.t.} & \underline{P}_b \leq \mathbf{P}_b \leq \bar{P}_b \\
& s_{\min} \leq \mathbf{s}_b \leq s_{\max} \\
& s_b^{t+1} = s_b^t + P_b \, \forall t = 0, \ldots, N-1 \\
& \underline{P}_s \leq \mathbf{P}_s \leq \bar{P}_s \\
& \underline{\delta}_s \leq \delta \mathbf{P}_s \leq \bar{\delta}_s \\
& \mathbf{P}_m = \mathbf{u}_m^{\cdot - \delta_m} \\
& \mathbf{e} = \mathbf{P}_b + \mathbf{P}_s - \mathbf{P}_m - \hat{\mathbf{a}}
\end{array}
\tag{8}
$$

where ρ_f is the terminal cost penalizing the distance of the state of charge to the reference state of charge.

Plus multi-objective cost to prioritize usage of the resources. At the end,some clever tuning of the cost function required.

It is important to notice that the performance of the system in providing a certain level of flexibility is not only dependent on the system limitations but also on the performance of the controller, which in turn depends on the performance of the prediction. For this reason, the same forecasts are always used for the same requests, independently of the system configuration considered. Secondly, the tuning of the controller was performed with caution in order to obtain homogeneous performance with a single controller tuning across the system parameters range.

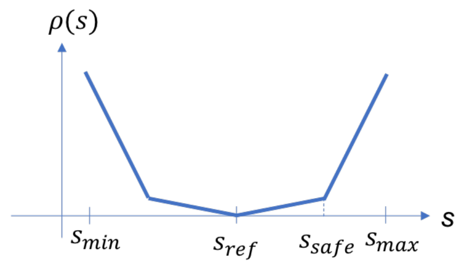

Figure 2: Terminal cost on state of charge. It is designed to favour SoC close to the reference with piecewise affine shape penalizing strongly SoCs close to the maximum and minimum allowed SoCs.

4 Opportunity of combining virtual storage and batteries

In this section, we examine the effect of the virtual storage characteristics on its potential to offer flexibility in combination with a battery system.

Figure 4 illustrates the joint operation of the virtual storage and battery by the controller over the span of a particularly extreme tracking event. In this example, the virtual storage in operated with a sampling time of 5 minutes and a maximum power of 1MW, while the battery has a 1 MWh storage capacity. We see that during hte extreme event, between hours 155 and 157, the virtual storage is used to discharge the battery that came to be practically full.

In the following, we study the effect of each parameter separately using as a benchmark the performance of the battery system alone. In order to measure the technical performance of the system, we use as a metric the maximum flexibility level that can be offered over the lifetime of the combined system.

4.1 Illustration of level of performance calculation

In order to decide if the performance of the system is acceptable, a maximum level of tracking error is fixed as a proportion of the flexibility offered. This statistics is computed as the average hourly absolute tracking error normalized by the amount of flexibility offered. For a fixed virtual storage + battery configuration, the ability of the system to maintain service decreases as the level of service required increases. This translates into an increase in the tracking error. Figure 3 illustrates the level of error experienced by the system as a function of the flexibility offered and gate closure delay.

Considering now this maximum error threshold, it is possible to extrapolate the maximum level of flexibility that can be provided by a given system configuration. Figure 5 illustrate this relationship.

As maintaining service is very important, we fix this threshold so that

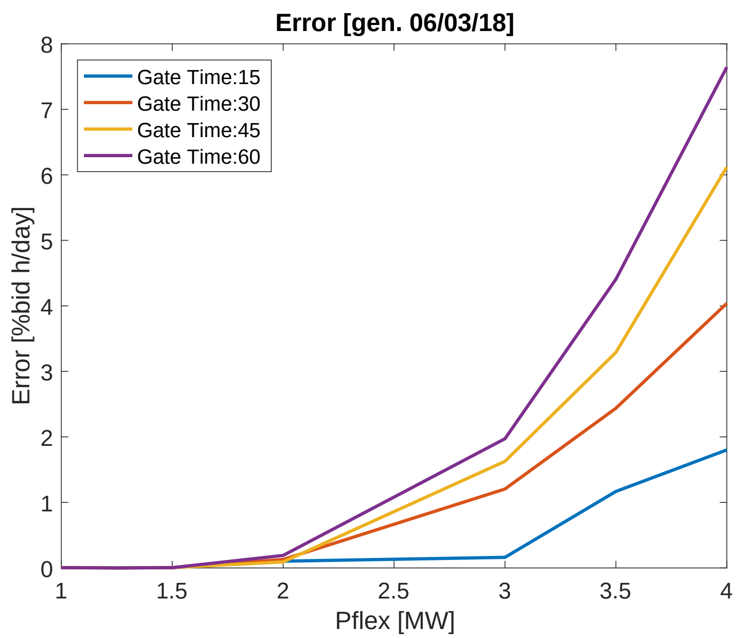

Figure 3: Tracking error as a function of flexibility and gate closure delay

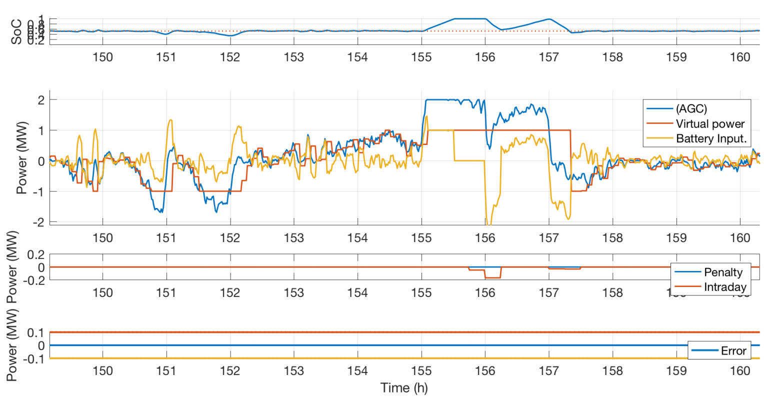

Figure 4: Time plot for illustration

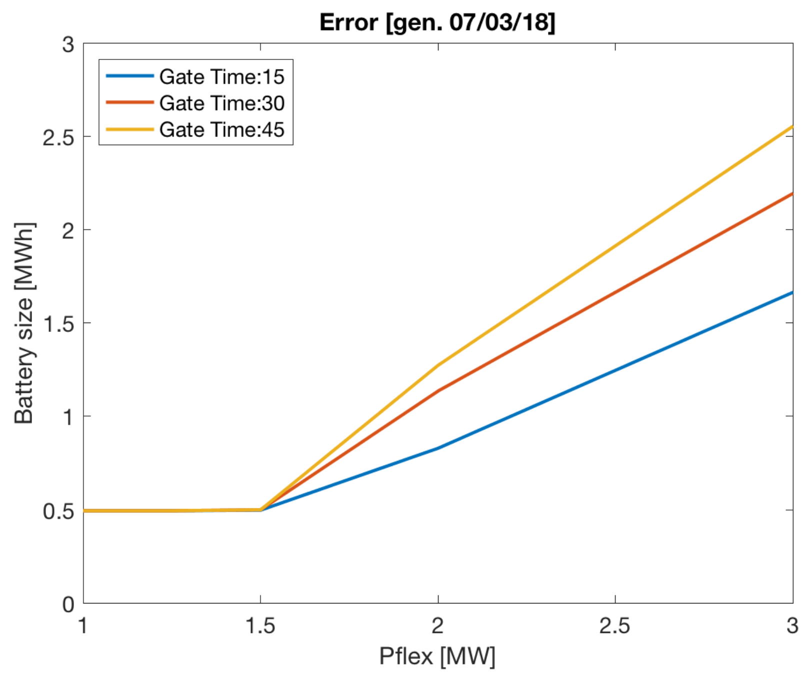

Figure 5: Minimum battery storage capacity size required as a function of flexibility offered and gate closure delay time.

Table 1: Achievable capacity for 1MWh battery and resulting battery life.

Delay [min]	Flex. Max. [MW]	TCL [MWmonths]	Batt. life [months]
30	0.77	98	147
60	0.35	59	180

the performance of the system is deemed acceptable if it incurs tracking errors less than 1% of the bid for one hour per day on average.

Remark 1. *It is worth noticing that errors will be zero on most days and will concentrate during 'adversary events' where the tracking request is particularly demanding, or when the forecast was particularly mistaken*

Based on the maximum flexibility offered by the system and on the basis of yearly control simulation, we evaluate the resulting battery life. Ageing of the battery uses the model developed by Omar et al. [2014] and considers the effect of cycling at different power levels on the battery state of health. As a consequence, we compute the total capacity over lifetime (TCL), which is computed as the sum of the capacity offered by the system on a monthly basis over its total lifetime, measured in MW.months. The computation of the TCL takes into account the decrease in flexibility that the system can offer as a result of the reduction of the battery capacity over time.

4.2 Benchmark study of battery alone

Here we detail how much flexibility can a battery offer alone. This depends only on the gate closure time.

Table 1 reports the maximum achievable flexible capacity, battery life and TCL that a fixed 1 MWh battery can offer as a function of the gate closure delay. The gate closure delay is the delay with which it is allowed to sell energy on the intraday market, measured in minutes; or more generically the delay with which we assume the battery can be discharged or recharged to balance its state of charge. Naturally, the shorter this delay, the more flexible capacity a battery can offer since it has less chance to get completely charged or discharged.

4.2.1 Sensitivity study of virtual storage characteristics

We consider here a 1 MWh virtual storage, and evaluate how much flexibility can be offered when different levels of battery are operated in combination with this virtual storage. To this end we simulate the combination of this virtual storage with batteries of size in the range $[0.25, 0.5, 1, 2, 4]$ MWh. We report here the maximum flexibility that the combined system can offer, compared to the battery alone.

Figure 6 reports the maximum capacity achievable as a function of the battery size for different values of the control time step of the virtual storage, while Figure 7 reports the corresponding battery life. We see that while the differences in time steps create small differences in capacity achievable, in particular virtually no difference when moving from a 1

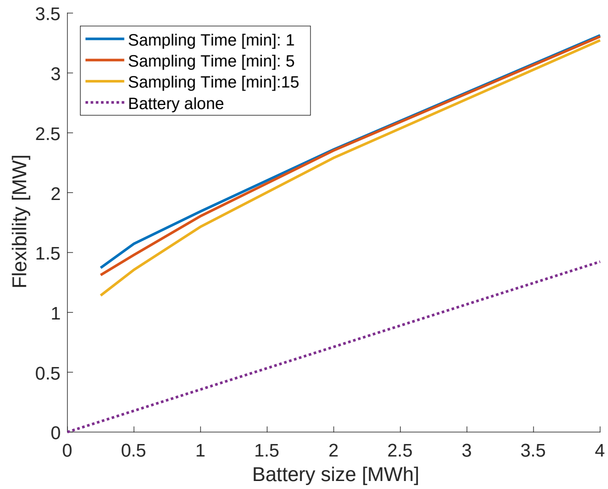

Figure 6: Maximum flexibility that can be offered as a function of battery size.

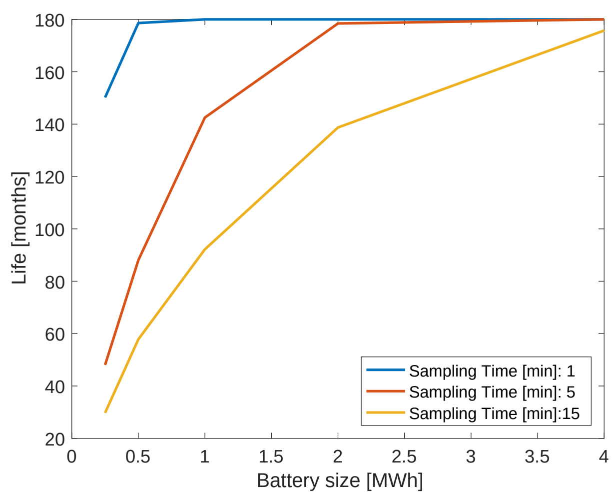

Figure 7: Life of the battery as a function of battery size at maximum capacity provided.

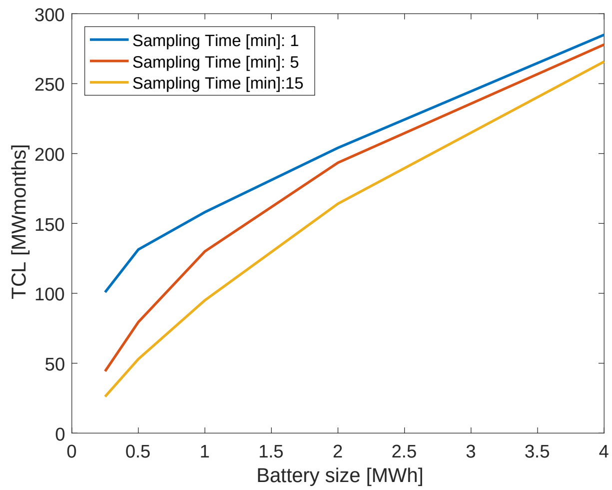

Figure 8: Total capacity over lifetime as a function of battery size.

minute to a 5 minute time step, it reflects strongly on the battery life. This makes sense as for the same level of capacity provided, a drop from 1 minute control time step to 5 minute will cause the battery to have to cover all signal changes faster than five minutes, and therefore cause significantly more cycling, and hence battery aging. This reflects in the total capacity over lifetime reported in Figure 8.

Similarly, we report the same results for varying ramping rates of the virtual resource in figures 9, 10 and 11. The same trend can be observed: while changes in ramping rate have very little influence on the achievable capacity, Dropping the ramping rate to 15 minutes significanlty reduces the life of the battery.

5 Financial analysis

In this section, we give details on different approaches that can be used to analyze the economic viability of different system configurations. We describe here a method to perform a simplified economic analysis considering the revenues and costs generated by providing flexibility, and the investment cost necessary to acquire the resources that guarantee the physical delivery. It is to be noted that while costs and revenues can be estimated relatively accurately on the basis of available data regarding flexibility payments and energy costs, the evaluation of the total investment cost is intrinsically case dependent, in particular for the virtual storage.

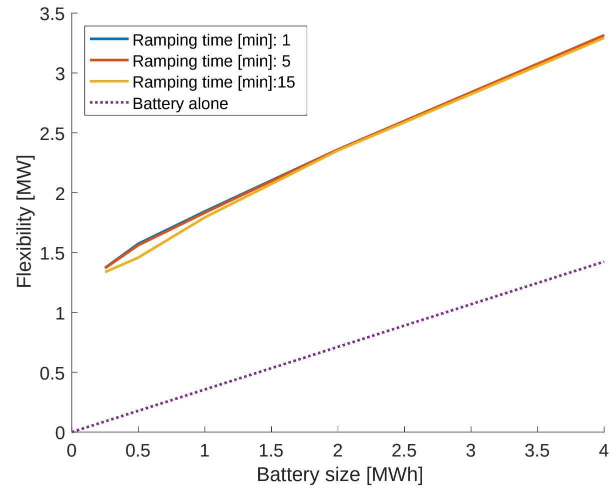

Figure 9: Maximum flexibility that can be offered as a function of battery size.

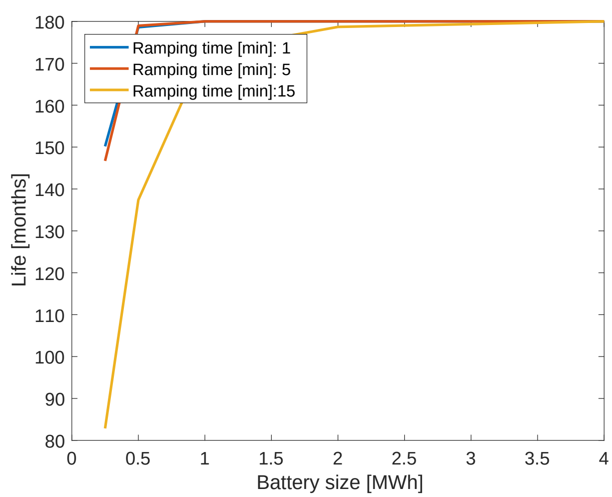

Figure 10: Life of the battery as a function of battery size at maximum capacity provided.

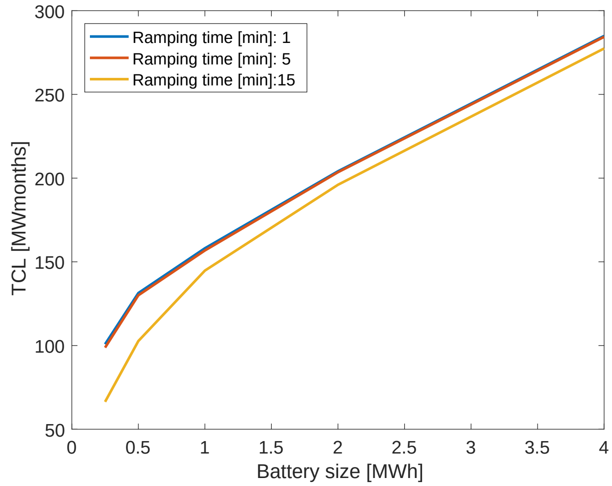

Figure 11: Total capacity over lifetime as a function of battery size.

5.1 Revenues and costs

For a particular configuration of the system, we compute annualized revenues and costs generated by the system over a year. In general, these estimates depend strongly on the application and local market conditions. We give here a simplified cost and revenue analysis for the provision of SFC in Switzerland.

Revenues

Providers of secondary frequency control are remunerated proportionately to the flexible capacity they provide, with a capacity payment in CHF/MW provided.

Costs

Even when the AGC is distributed around 0, the roundtrip efficiency of the battery requires to recharge the battery periodically in order to compensate for roundtrip losses. This results in a net energy consumption which causes energy and distribution costs.

For a particular configuration of the system, we compute annualized revenues and energy costs. To perform this computation, average energy index prices are considered, as well as average historical AGC prices, assuming a utilization of the system of 50 weeks per year.

Finally, we consider operating costs for the system. Since operating costs for different resources are difficult to evaluate, we consider operating costs in proportion to the investment (2%)

5.2 Investment costs

The cost of acquisition of the battery and the virtual storage are treated separately. The cost of the battery is broken down in two main components:

- AC costs: this costs are proportional to the total maximum power of the battery system installed and include the inverters and installation of the battery systems.
- DC costs: this costs are proportional to the total maximum storage capacity of the battery installed and include the cost of the battery cells and packaging.

Evaluating the cost of the virtual storage is very case-dependent and could vary largely depending on the assumptions regarding this resource. We adopt a simplified analysis that evaluates the cost of acquisition of the virtual storage in mCHF/MW. Note that the method described below can be used with various economic assumptions on the virtual storage. (fixed cost of acquisition/ no cost / increasing marginal cost of acquisition)

5.3 Results

The plots reported in section 4.2.1 contain all the information about the technical capability of different system configurations. Combined with the following financial information, it allows us to inform investment decisions by calculating the financial return of a project.

- Investment cost model in batteries
- Investment cost model in virtual storage
- Budget

Based on past price data for power reserves in the Swiss market and as reported in Qureshi et al. [2014], we have observed that capacity payments represent the majority of revenues when providing ancillary services, with respect to the costs energy costs involved. As a consequence, to maximize revenues, the flexible capacity offered should be maximized. This assumption is followed throughout the financial analysis. For given system characteristics, we have a total investment cost $I(s_{\max}, \bar{P}_s \bar{P}_b)$. Based on a price for flexible capacity c_{flex}, revenues from capacities are computed as detailed in section 5.1. Compiling this and aging characteristics, monthly revenues from capacities are computed, as well as distribution costs and operational costs. The resulting net present value and internal rate of return can then be computed.

In the simplest case, we consider the investment as a linear function of the virtual storage size and the battery storage capacity acquired so that:

$$I(p_{\max}, s_{\max}) = c_{\text{batt}} s_{\max} + c_{\text{res}} p_{\max} \tag{9}$$

where c_{batt} the cost of batteries in CHF/MWh and c_{res} the price of virtual storage in CHF/MW.

Figure 12 shows the internal rate of return as a function of the relative cost of acquisistion of virtual storage and batteries, and the battery to virtual storage ratio.

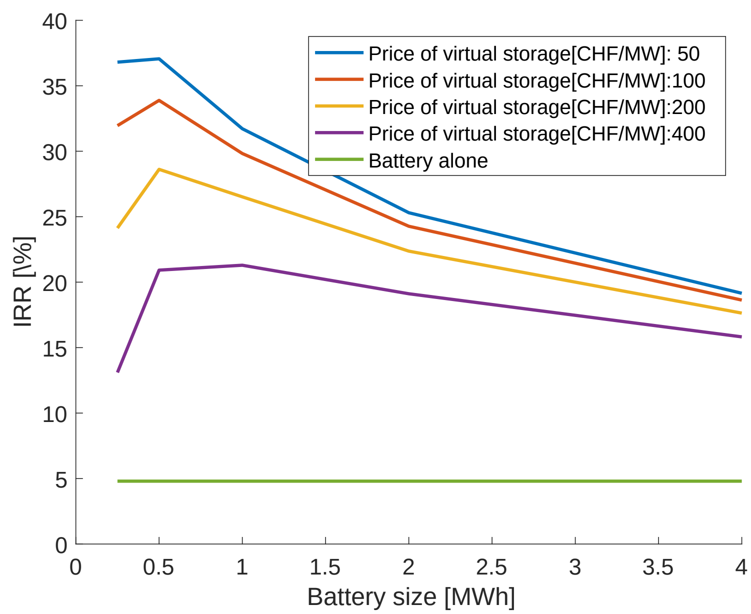

Figure 12: IRR as a function of battery size and price of virtual storage

We see that as the virtual storage gets relatively more expensive, it attracts less investment for an optimal investment decision. This figure reports results assuming a battery cost of 700 CHF/Mwh and considers the virtual storage with a 15 minutes ramp limitation.

6 Conclusion

This paper presents a method to evaluate the potential of the combination of energy resources with heterogeneous technical and economic characteristics to provide grid services. This method considers simple characterizations of the resources based on models including key dynamic characteristics and operational constraints of the resources such as sampling frequency, energy storage, ramp and power limits. We particularly focus here on the effect of these characteristics on the ability of the systems to collectively provide power consumption tracking. To study this, we propose an MPC control architecture to approximate the optimal controller behavior, and on the basis of system control simulation, determine technically achievable levels of power consumption tracking the system can support. Finally, it offers a simplified economic analysis framework to evaluate the economic performance of the system over its lifetime, using operational and investment costs for the systems. The article particularly focuses on the combination of batteries and other technically constrained resources to offer secondary frequency control in Switzerland, using real service data. This capacity highlights the benefit of combining the battery with other resources to boost the amount of tracking services provided, and evaluates the economic relevance of the combination of resources as a function of cost of acquiring resources with given technical characteristics. It also performs for this example a sensitivity analysis of the effect of key limiting characteristics on the overall system performance. It for examples reveals that while the effect of ramp rates of the slow resource of up to 15 minutes as a very limited effect on the system technical performance, it dramatically affects the battery life; and hence the economic relevance of the corresponding resources combinations.

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