Techno-economic optimization of services stacking for a battery participating to electricity spot markets

Andrea Scrocca, Filippo Bovera, Giuliano Rancilio, Maurizio Delfanti
Department of Energy, Politecnico di Milano
Milan 20156, Italy
andrea.scrocca@polimi.it

Matteo Zatti
LEAP s.c.a.r.l., Laboratorio Energia Ambiente Piacenza
Piacenza 29121, Italy

***Abstract*—This study explores the optimization of services stacking for a battery providing primary, secondary, and tertiary frequency regulation while participating in the day-ahead market in Italy. Formulated as a two-stage stochastic Mixed Integer Linear Programming (MILP) problem, the objective is to maximize daily revenues accounting for uncertainty related to tertiary reserve offers acceptance. The paper investigates how technical and financial market design parameters impact battery's revenues and optimal strategy. Key findings indicate that the highest economic gains are associated with batteries having intermediate Energy-to-Power Ratio (EPR): too high EPR increase the investment risk, and very low EPR are optimal only under specific market conditions. The study highlights the need for proper balancing capacity payments to incentivize batteries participation to flexibility markets. The market value of diverse services also drives investments choices in terms of batteries' design, specifically influencing the EPR value.**

***Index Terms*-- battery energy storage systems, ancillary services, stochastic optimization, market design**

I. Introduction

The European decarbonization strategy has structurally modified the power system, increasing the penetration of Non-Programmable Renewable Energy Sources (NP-RES). Consequently, it has become essential to develop storage systems capable of effectively decoupling energy production and consumption over time. Among the alternatives, Battery Energy Storage Systems (BESS), especially those utilizing lithium-ion technology, have emerged as the most promising solution. The application of this technology can be crucial, entailing both energy arbitrage and ancillary services provision.

Recognizing the importance of storage systems in the energy transition, it is necessary to build models capable of optimizing their design and real-time operations within electricity markets. Indeed, such models can serve as tools to inform investors and policymakers.

A comprehensive review of existing literature reveals diverse approaches to this problem. In the study by Abiodun et al. [1] the profitability of a Concentrating Solar Power (CSP) plant providing spinning reserve in the ASM (Ancillary Services Market) is analyzed. The model optimizes system operations within both the Day-Ahead Market (DAM) and the ASM employing a 72h-rolling-horizon framework where perfect knowledge of day ahead pricing and solar resource availability is assumed. Schwidtal et al. [2] describe a Mixed-Integer Linear Programming (MILP) model to optimize the operations of a P2G (Power-to-Gas) system aggregated with PV, considering varying degrees of interaction with the electricity markets. In particular, the revenue coming from DAM, IDM (Intraday Market), secondary reserve, tertiary reserve and passive balancing are contemplated. To formulate the bidding strategy across these markets, a multi-stage and multi-period optimization approach is used. Lai et al. [3] formulated a MILP to optimize the operations of an Integrated Energy Service Provider (IESP). The objective is to select the optimal capacity allocated for ancillary services to maximize daily revenues.

In particular, many studies focused on optimizing battery exploitation in markets. Ai et al. [4] developed a robust optimization model for a wind/battery power plant, accounting for uncertainties associated with wind resource forecasting and ancillary service demand. Feng et al. [5] introduced a multi-objective and multi-level model that optimizes the participation to DAM and the provision of tertiary reserve by a wind/PV power plant integrated with a battery. In the study by Naemi et al. [6] the optimization pertains to the design and operations of a BESS integrated into a wind power plant. The interaction with the Australian energy market and ASM is considered. Fusco et al. [7] presented a multi-stage stochastic MILP model with binary recourse strategies. The aim is to optimize the operations of virtual power plants taking into account uncertainties related to renewable production forecasting and ancillary services market demand.

From this literature review, it is evident that BESS design and operations optimization in the case of ancillary services provision has been extensively studied. However, few studies have implemented stochastic optimization to consider the uncertainty related to balancing offers acceptance. Furthermore, none of the identified studies investigated the optimization of the simultaneous provision of primary, secondary, and tertiary frequency regulation services, assessing the impact of different markets' design options.

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The purpose of this paper is to introduce a model that optimizes the operations of a BESS simultaneously providing different ancillary services and participating in the day-ahead market (DAM), considering Italian market framework as a reference case study. The considered ancillary services are Frequency Containment Reserve (FCR), also known as primary reserve; automatic Frequency Restoration Reserve (aFRR) or secondary reserve; manual Frequency Restoration Reserve (mFRR) and Replacement Reserve (RR), also addressed as tertiary reserve. The primary objective is to assess the variability of BESS revenues and optimal operations on different days and under different market design options. The analysis will specifically evaluate the impact of:

- market prices, grid frequency, and Area Control Error (ACE) data;
- the ratio between battery's nominal energy and power, known as Energy-to-Power Ratio (EPR);
- market design parameters such as the minimum required duration of tertiary regulation $Tmin^{ter}$, the possibility of offering aFRR asymmetrically, and balancing capacity payments for FCR and aFRR.

The remainder of the paper is organized as follows. Chapter II introduces the modelling of the battery, as well as of the interactions with all the electricity markets. Chapter III presents the analyzed case studies and the discussion of obtained results. Finally, the main findings are listed in Chapter IV together with suggestions for future research advancements.

II. System Modelling

The formulation of the problem adopts a two-stage stochastic MILP framework. In a two-stage stochastic problem, it is possible to identify an uncertain event for which all possible realization scenarios and associated probabilities are known in advance. Variables that are determined before this uncertain event are referred to as first-stage or "here and now" variables, while those known only after the resolution of uncertainty are called second-stage or "wait and see" variables [8]. In the analyzed problem the uncertain event is the acceptance of the offers presented for tertiary power regulation. The first-stage variables are the ones defining the BESS daily commercial program on the markets: FCR and aFRR offered daily power bands, DAM and tertiary reserve quarter-hourly power fluxes. Second-stage variables encompass all the variables that define real-time operations of the battery, influencing the actual charging/discharging power flows and state of charge. Obviously, for each scenario, revenues resulting from tertiary regulation will be different depending on which offers have been accepted. The objective function to maximize is the average revenue value across all scenarios weighted by their respective probabilities. The intent is to determine the daily commercial program that, on average, would yield the maximum revenue. An overview of the two-stage stochastic problem is shown in Fig. 1.

Two modelling frameworks are considered in this study. The first will be called "basic" model. It represents the conventional design parameters of the Italian ASM. Instead, the second modelling framework considers some modifications aimed at making ancillary services more economically attractive for batteries. This modelling will be referred to as the "modified" model. The essential changes are twofold:

- FCR and aFRR are not compensated solely based on the processed energy but also on the power band offered for the service (the capacity compensation mechanism is not currently adopted in the Italian grid code but is considered for future implementation);
- secondary reserve can be offered with asymmetric power bands for upward and downward services.

The latter market regulation is already included in the Italian grid code, but it was introduced only recently (March 2023) [9].

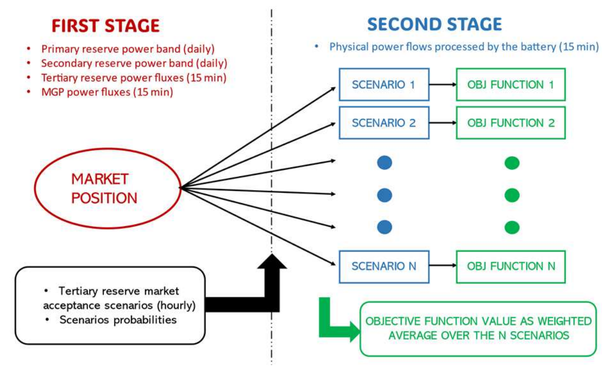

Figure 1- Structure of the Optimization Problem

1) *Battery Model*

The chosen model for the battery is a stepwise model with constant efficiencies that depend on the power processed by the battery, as illustrated in Fig. 2.

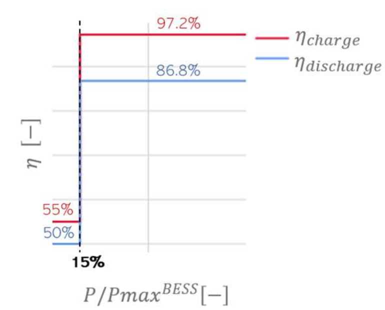

Figure 2-BESS Model Efficiency Values

Among various models in the literature, the specific choice of this model is supported by the studies [10] and specifically [11], where Rancilio et al. investigated the performance of a Li-ion Battery in relation to state of charge (SOC) and processed power. Results reveal that efficiencies decline sharply when the battery processes excessively low powers, while the dependence on the SOC is minor. Equation (1) shows how the stepwise efficiency behavior has been modelled:

$$soc^{BESS}_{sc,h,q} == soc^{BESS}_{sc,(h,q)_{pre}} + p^{cha_{a15}}_{sc,h,q} * \eta^{cha_{a15}} + p^{cha_{b15}}_{sc,h,q} * \eta^{cha_{b15}} - \frac{p^{dis_{a15}}_{sc,h,q}}{\eta^{dis_{a15}}} - \frac{p^{dis_{b15}}_{sc,h,q}}{\eta^{dis_{b15}}} \quad (1)$$

2) *Electricity Markets Model*

The following equations are referred to the "basic" model. The "modified" model equations, which differ from the following ones, are shown in Appendix B. All variables and parameters employed in this document are outlined in Appendix A.

For the DAM, a price-taker approach is assumed, where offers to buy or sell are always accepted and compensated at the hourly price for the NORD market zone. When buying/selling in the DAM, it is not necessary to withdraw/inject power constantly over the hour under analysis. Instead, flexibility is allowed to process varying power flows during each of the four 15-minute intervals within the hour, as long as their average value is consistent with the hourly offer (2). This choice is made to enable the DAM power flows to adapt to the fluctuations in primary and secondary reserve power flows, which can change on a 15-minute basis.

$$p_h^{sold} == \sum_q^Q \frac{p_{h,q}^{sold_{qrt}}}{4}\, ;\, p_h^{purch} == \sum_q^Q \frac{p_{h,q}^{purch_{qrt}}}{4} \qquad (2)$$

According to the Italian grid code [12], primary regulation is automatically provided by all the enabled units whenever the frequency value exceeds the fixed dead-band boundaries (50Hz-20mHz < f < 50Hz+20mHz) and proportionally to the deviation from the nominal value Δf (3).

$$\Delta P_e = -\frac{\Delta f}{50} \cdot \frac{P_{eff}}{\sigma_p} \cdot 100 \qquad (3)$$

Where P_{eff} is the efficient unit power and σ_p is a technical parameter of the device controlling the provision of the service. If the frequency exceeds 50Hz+20mHz, the production unit decreases the produced power ("downward" service) by ΔP_e; if it falls below 50Hz-20mHz, the unit increases power ("upward" service) by ΔP_e. Equation (3) allow us to compute the FCR activation per unit of offered power band. For the sake of simplicity, since primary regulation is a continuously changing set-point, FCR was included in the problem considering the average activation over each quarter-hour $PERC_{h,q}^{prim}$ and computing FCR power flows on a 15-minutes basis. Within the structure of the studied optimization problem, the daily allocated FCR power band $p^{band_{prim}}$ is the optimization variable for the primary regulation service. The processed power flows are determined as in (4), where $Y_{h,q}^{prim_{UP}}$ and $Y_{h,q}^{prim_{DW}}$ are binary parameters defining the direction of activation.

$$\begin{aligned} p_{h,q}^{prim_{UP}} &== \frac{PERC_{h,q}^{prim}}{100} * p^{band_{prim}} * Y_{h,q}^{prim_{UP}} \\ p_{h,q}^{prim_{DW}} &== \left|\frac{PERC_{h,q}^{prim}}{100}\right| * p^{band_{prim}} * Y_{h,q}^{prim_{DW}} \end{aligned} \qquad (4)$$

The aFRR is automatically activated based on the ACE (Area Control Error) value which is communicated by the TSO every minute. From the ACE, it is possible to easily compute the activation of the offered secondary power band for each minute; despite this, also aFRR was simulated in the problem based on a 15-minutes based activation. In this case as well, the only optimization variable is the offered power band, and for the "basic" model, equations to calculate the quarterly power flows are analogous to those seen for FCR in (4).

In the case of tertiary reserve, according to the Italian grid code, there is no automatic activation of a predefined power band. Instead, each enabled unit can submit bids in the ASM with specified prices and quantities for each hour. If accepted by the TSO, these bids can be activated in real-time. To model the provision of this service, the following approach was implemented. For each hour, there is the possibility to decide whether to offer tertiary reserve in an upward direction, a downward direction, or neither. The offered power for each hour is an optimization variable ($p_h^{ter_{UP}}$ and $p_h^{ter_{DW}}$), while the offered price, denoted as $OFFER_h^{ter_{UP}}$ or $OFFER_h^{ter_{DW}}$, is a parameter. The binary parameters $Y_{sc,h}^{ter_{UP_{par}}}$ or $Y_{sc,h}^{ter_{DW_{par}}}$ represent the acceptance of the offers and generates six different market scenarios, with different occurrence probability. The actual power processed in each scenario *sc* is equal to the product between the offered power and the binary parameter: zero if the offer is not accepted, and the offered power if the offer is accepted. This energy is compensated at the offered price and it contributes to the total revenues of the battery based on the probability of occurrence of the considered scenario. The parameters $Y_{sc,h}^{ter_{UP_{par}}}$ and $Y_{sc,h}^{ter_{DW_{par}}}$ were generated using a tool developed in ref. [13]. Finally, a guaranteed minimum duration $Tmin^{ter}$ of the tertiary reserve service was considered. This was done through the definition of constraints checking the battery SOC which are reported in Appendix B. The next step is to describe how these diverse operations within the DAM and the ASM are integrated together. First, it is crucial to ensure that the combined upward and downward commercial positions do not overcome the battery power rating (*5*). Then a limit on the physical power processed by the battery must be defined (6). Subsequently, a power balance connecting commercial and physical variables is defined (7).

$$\begin{aligned} p^{band_{prim}} + p^{band_{sec}} + p_h^{ter_{UP}} + p_h^{sold} &\le Pmax^{BESS} \\ p^{band_{prim}} + p^{band_{sec}} + p_h^{ter_{DW}} + p_h^{purch} &\le Pmax^{BESS} \end{aligned} \qquad (5)$$

$$p_{sc,h,q}^{BESS_{abs}} \le Pmax^{BESS} \qquad (6)$$

$$\begin{aligned} p_{sc,h,q}^{dis} - p_{sc,h,q}^{cha} == &\left(p_{h,q}^{sold_{qrt}} - p_{h,q}^{purch_{qrt}}\right) \\ &+ \left(p_{h,q}^{prim_{UP}} - p_{h,q}^{prim_{DW}}\right) \\ &+ \left(p_{h,q}^{sec_{UP}} - p_{h,q}^{sec_{DW}}\right) \\ &+ \left(p_{h,q}^{ter_{UP_{qrt}}} * Y_{sc,h}^{ter_{UP_{par}}} \right. \\ &\left. - p_{h,q}^{ter_{DW_{qrt}}} * Y_{sc,h}^{ter_{DW_{par}}}\right) \end{aligned} \qquad (7)$$

Finally, the objective function is described by (8).

$$\begin{aligned} &\sum_{sc=1}^{6} P_{sc}^{scenario} * \sum_{h=1}^{24} \left(p_h^{ter_{UP}} * Y_{sc,h}^{ter_{UP_{par}}} * OFFER_h^{ter_{UP}} - \right. \\ &\left. p_{h,q}^{ter_{DW}} * Y_{sc,h}^{ter_{DW_{par}}} * OFFER_h^{ter_{DW}}\right) + \sum_{h=1}^{24}\sum_{q=1}^{4}\left(\frac{p_{h,q}^{prim_{UP}}}{4} * \right. \\ &\left. PRICE_h^{prim_{UP}} - \frac{p_{h,q}^{prim_{DW}}}{4} * PRICE_h^{prim_{DW}}\right) + \sum_{h=1}^{24}\sum_{q=1}^{4}\left(\frac{p_{h,q}^{sec_{UP}}}{4} * \right. \\ &\left. PRICE_h^{sec_{UP}} - \frac{p_{h,q}^{sec_{DW}}}{4} * PRICE_h^{sec_{DW}}\right) + \sum_{h=1}^{24}\left(p_h^{sold} - p_h^{purch}\right) * \\ &PRICE_h^{DAM} + \sum_{sc=1}^{6} P_{sc}^{scenario} * \frac{(soc_{sc,24,4}^{BESS} - 50)}{100} * E^{BESS} * \\ &PRICE^{DAM_{REF}} \end{aligned} \qquad (8)$$

III. Case Studies and Results

The problem was initially solved on two typical days, each characterized by significantly different market price values. These specific days are June 24, 2021, and December 16, 2021.

The analysis was first conducted for the "basic" scenario, considering a 1MW-rated battery with varying EPR values (1,2,4,6 or 8). Simultaneously, for each of the five EPR values, different $Tmin^{ter}$ values (ranging from 1 to 4 hours) were taken into account. Subsequently, the "modified" model was also solved for the same scenarios. Examining the results for the two typical days allowed for an investigation into the impact of the market parameters. However, examining only these results does not allow for drawing general conclusions about the economic profitability and optimal behavior of the battery under the two modelled market designs, and under varying EPR and $Tmin^{ter}$. To gain a more comprehensive understanding, a Monte Carlo approach was adopted, and a set made by 100 random days within the timeframe of March 2021 to June 2023 was selected. For each of these days, both the "basic" and "modified" models were solved across the 20 EPR and $Tmin^{ter}$ scenarios.

To analyze the battery economic results, the behavior of two parameters is investigated. Firstly, the specific revenues per installed MWh are considered. The second parameter is the Net Present Value (NPV), calculated as outlined in (9).

$$NPV = -CAPEX + \sum_{t=1}^{10}\left(\frac{Revenues\left[\frac{€}{day}\right]*365[day]-OPEX}{(1+i)^t}\right) - \sum_{t=1}^{10}\left(\frac{CAPEX_{newBESS}}{(1+i)^t}\right) + RV \qquad (9)$$

This computation spans a 10-year time horizon with a fixed discount rate i of 5%. When computing the NPV, the assumption is that the battery's daily behavior remains consistent, resulting in a constant daily revenue over the 10-year period. The capital expenditure (CAPEX) is computed considering both an energy component (k_e=250k€/MWh) and a power component (k_p=80k€/MW). The operational expenses (OPEX) are set at 5k€/MWh/year [14]. To account for cycling ageing, it is imposed that if the number of cycles conducted by the battery on the typical day exceeds a 5000-cycle threshold [15] within the 10-year period, an additional expenditure is considered equal to the energy component of the CAPEX. An economic residual value (RV) for the battery is also considered.

Regarding the input data sources, the following references were used. Frequency data were obtained from measurements conducted at the PoliGrid of Politecnico di Milano. ACE data were sourced from Terna's website [16]. Price data for energy compensation were gathered from GME's website [17]. The price data for capacity compensation, as they are not included in the Italian regulatory framework, were obtained from the website of the German system operator Regelleistung [18]. Tertiary reserve acceptance scenarios were generated using the tool of ref. [13]; input data for creating these scenarios were available from GME's [17] and ENTSO-E's [19] websites.

1) Results for two typical days

Analysis of the input data for the two selected typical days, shown in Appendix C, reveals significant differences. On December 16th, it is possible to observe greater DAM price fluctuations which makes energy arbitrage more convenient. Additionally, the greater differential between upward and downward aFRR energy prices increases the revenue coming from this service. Finally, a higher average differential between the DAM price and the downward mFRR price offer is observed. Consequently, it becomes more convenient to charge the BESS using the downward tertiary reserve service.

These disparities in market conditions are reflected in the economic results for the two typical days. Analyzing the trend of specific revenues as a function of EPR for the "basic" case, a bell-shaped curve is observed for both days, with the peak occurring at EPR=2. As shown in Appendix Fig. 4 and 5, what differs between the two days is the revenues volume, much greater on December 16th. Similar considerations are in place for the "modified" model, where the optimum shifts at EPR=1 as it can be seen from Appendix Fig. 6 and 7. Looking at the NPV for the two days under the "basic" model in Appendix Fig. 8 and 9, it is remarkable that on June 24th the NPV results are always negative, while for December 16th the investment proves to be consistently profitable. Additionally, it is possible to observe different NPV behaviors as function of EPR. On June 24th, EPR=2 is the optimum condition, while on December 16th, EPR=8 maximizes the NPV. The factor behind this different behavior is the DAM price. Indeed, increasing EPR essentially allows for offering more tertiary reserve and exchanging more energy on the DAM. Consequently, the higher investment required at higher EPR values will be positively repaid only if these two interactions with the electricity markets are sufficiently advantageous. Since having high DAM prices with significant fluctuations throughout the day makes energy arbitrage on DAM and offering tertiary downward reserve highly advantageous, it becomes clear why increasing EPR becomes favorable in market situations like those of December 16th. Looking at the NPV values obtained for the "modified" model in Appendix Fig. 10 and 11, it is evident that the values are still significantly higher for December 16th. However, the "modified" framework makes the investment advantageous even under conditions like those of June 24th. The optimal EPR differs between the two days: on June 24th, EPR=1 emerges as the most favorable condition due to capacity payments and the ability to asymmetrically provide aFRR; on December 16th, as it was for the "basic" model, the optimal situation is given by EPR=8.

2) Results for the Monte Carlo simulation

From the Monte Carlo simulation results it is possible to draw more general conclusions regarding the BESS behavior. Economic outcomes and optimal strategy are strongly influenced by EPR. Instead, $Tmin^{ter}$ has a negligible impact, with the sole exception of slightly reducing the offered power for tertiary reserve. For example, Fig. 3 and 4 depict the impact of EPR and $Tmin^{ter}$, respectively, on the specific revenues obtained for the "basic" model.

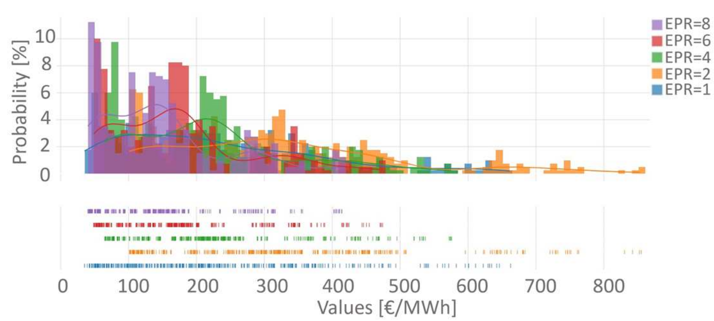

Figure 3 – "Basic" Revenue: EPR probability distributions.

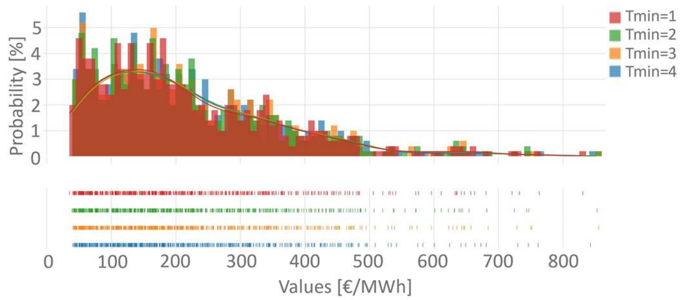

Figure 4- “Basic” Revenue: $Tmin^{ter}$ probability distributions.

Examining NPV outcomes, as shown in Fig. 5 and 6, it is possible to observe that EPR=2 and 4 are generally the optimum situations in both models. EPR=1 becomes a convenient condition only when transitioning to the “modified” model, while it is the worst for the “basic” model. The risk of negative NPVs is higher for higher EPR, especially in the “basic” modelling. However, at EPR=6 and 8, the highest NPVs can be achieved if market conditions are favorable.

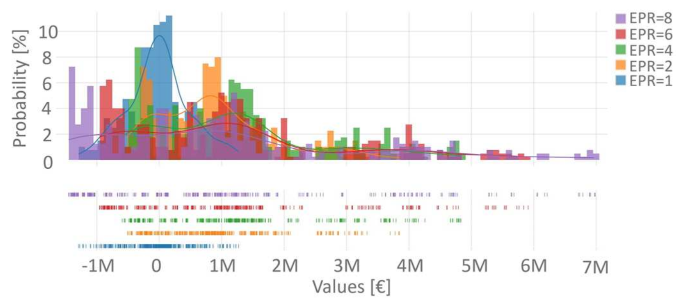

Figure 5 – “Basic” NPV: EPR probability distributions.

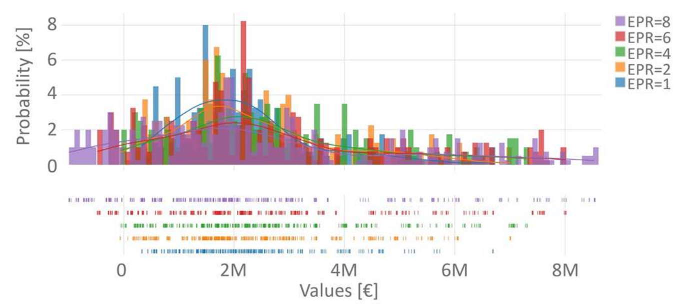

Figure 6 – “Modified” NPV: EPR probability distributions.

Results indicate that FCR is the least advantageous in the services stacking context. In the “basic” model it is employed only in 5 instances out of 2000, and even in the “modified” model the occurrences are only 57. This phenomenon can be explained by the infrequent activation of FCR and by the fact that the average price differential between its upward and downward prices in €/MWh is considerably smaller than the one for aFRR. Examining the utilization of other services at varying EPR for the “base” case reveal the following observations. At EPR=1, there is a limitation in offering secondary and tertiary reserve due to energy limitations. At EPR=2 and 4, the available power band is effectively utilized, mainly for aFRR. At EPR=6 and 8, the secondary power band is slightly reduced to offer more tertiary reserve, indicating limitations imposed by the installed power. On the other hand, for the “modified” case, at EPR=1, the power band is more extensively utilized than in the “basic” model due to the ability to offer aFRR asymmetrically. At EPR=2 and 4, there is still efficient utilization of installed power and energy, with a certain asymmetry between upward and downward aFRR power bands. A higher power band is offered in the upward direction because tertiary reserve is predominantly accepted downward. This asymmetry increases at EPR=6 and 8 because more tertiary reserve is offered.

IV. Conclusions and Future Work

This research introduced a model aimed at optimizing services stacking by a battery operating within the Italian electricity spot markets. The primary focus has been on analyzing the variability of economic outcomes and optimal strategy under varying boundary conditions. The study reveals that the incorporation of capacity remuneration for FCR and aFRR is essential to mitigate investment risks. The transition from the “basic” to the “modified” model shows a noteworthy reduction in the occurrence of cases where Net Present Value (NPV) falls below zero: from 32% to 5%. Furthermore, our findings highlight the substantial impact of the Energy-to-Power Ratio (EPR) on the economic performance of the battery. Optimal scenarios emerge particularly at EPR values of 2 and 4, for which high average NPV, minimal variance, and a diminished risk of NPV lower than zero are observed. Increasing EPR at 6 or 8 could potentially lead to enhanced outcomes, but concurrently it introduces higher variability, exposing more the battery profitability to the market prices. The condition EPR=1, considered the least favorable in the "basic” model, achieves economic comparability with EPR=2 and 4 through the introduction of capacity remuneration and the ability to provide secondary reserve asymmetrically. Conversely, it is deduced that the duration of tertiary regulation provision $Tmin^{ter}$ exerts negligible influence on economic outcomes. Looking at the optimal battery strategy adopted for BESS operations, our investigation reveals that primary reserve service emerges as the least advantageous within services stacking. Even introducing capacity remuneration, FCR fails to compete with the other services (activated in only 3% of cases). Furthermore, the analysis highlights the challenges of services stacking with EPR=1 due to energy limitations. However, the option to asymmetrically offer aFRR increases the utilization of installed power for EPR=1. EPR=2 and 4 emerge as the optimal configurations, showing better synergy among diverse services and an optimal utilization of available resources. For EPR=6 and 8 it is possible to increase the power offered for tertiary reserve, but due to power limitations it is not possible to optimize completely all the stored energy.

In future research, a model with second-level discretization could be developed to simulate battery operations. The aim is to assess whether the activation of primary reserve at the second level and secondary reserve at the minute level allows for the feasibility of the scheduled commercial hourly program. Indeed, in this study, an average activation over a 15-minutes interval is considered, which underestimates the total energy exchanged in both directions by the battery. Furthermore, different simulations could consider the uncertainty related to the parameters describing the activation of services. Finally, the model could incorporate the economic regulation of imbalances and of non-compliance with dispatch orders for tertiary reserve.

ACKNOWLEDGMENT

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Appendix A: Nomenclature

Sets	
h	Hour of the day (from 1 to 24)
m	Minute in quarter q (from 1 to 15)
q	Quarter-of-hour in hour h (from 1 to 4)
s	Second in minute m (from 1 to 60)
sc	Market scenario (from 1 to 6)
Parameters	
$CAPEX$	BESS capital expenditure [€]
E^{BESS}	Battery capacity [MWh]
EPR^{BESS}	Battery Energy-to-Power Ratio [-]
$Ncycles^{BESS}$	Battery max number of cycles [-]
$OFFER_h^{ter_{UP}}$	Upward tertiary reserve energy price offer [€/MWh]
$OFFER_h^{ter_{DW}}$	Downward tertiary reserve energy price offer [€/MWh]
$OPEX$	BESS operational expenses [€]
$PERC_{h,q,m,s}^{prim}$	Primary band activation on s [%]
$PERC_{h,q}^{prim}$	Average primary band activation on q [%]
$PERC_{h,q,m}^{sec}$	Secondary band activation [%]
$PERC_{h,q}^{sec}$	Average secondary band activation on q [%]
$Pmax^{BESS}$	Battery power rating [MW]
$PRICE_h^{cap_{prim}}$	Primary reserve capacity price [€/MW]
$PRICE_h^{cap_{sec_{UP}}}$	Upward secondary reserve capacity price [€/MW]
$PRICE_h^{cap_{sec_{DW}}}$	Downward secondary reserve capacity price [€/MW]
$PRICE_h^{DAM}$	DAM price [€/MWh]
$PRICE_h^{prim_{UP}}$	Upward primary reserve energy price [€/MWh]
$PRICE_h^{prim_{DW}}$	Downward primary reserve energy price [€/MWh]
$PRICE_h^{sec_{DW}}$	Downward secondary reserve energy price [€/MWh]
$PRICE_h^{sec_{UP}}$	Upward secondary reserve energy price [€/MWh]
$P_{sc}^{scenario}$	Market scenario probability [-]
RV	BESS residual value [€]
T^{BESS}	Battery expected lifetime [years]
$Tmin^{ter}$	Guaranteed duration of tertiary reserve [h]
$Y_{h,q}^{prim_{DW}}$	Binary parameter=1 if $PERC_{h,q}^{prim}$<0 [-]
$Y_{h,q}^{prim_{UP}}$	Binary parameter=1 if $PERC_{h,q}^{prim}$>0 [-]
$Y_{h,q}^{sec_{DW}}$	Binary parameter=1 if $PERC_{h,q}^{sec}$<0 [-]
$Y_{h,q}^{sec_{UP}}$	Binary parameter=1 if $PERC_{h,q}^{sec}$>0 [-]
$Y_{sc,h}^{ter_{DW_{par}}}$	Binary parameter =1 if downward tertiary offer is accepted in hour h and scenario sc [-]
$Y_{sc,h}^{ter_{UP_{par}}}$	Binary parameter =1 if upward tertiary offer is accepted in hour h and scenario sc [-]
Δf	Frequency deviation from the nominal value [Hz]
$\eta^{cha_{a15}}$	Charging efficiency if $p_{sc,h,q}^{cha}$ >0.15P_{max}^{BESS} [-]
$\eta^{cha_{b15}}$	Charging efficiency if $p_{sc,h,q}^{cha}$ <0.15P_{max}^{BESS} [-]
$\eta^{dis_{a15}}$	Discharging efficiency if $p_{sc,h,q}^{dis}$ >0.15P_{max}^{BESS} [-]
$\eta^{dis_{b15}}$	Discharging efficiency if $p_{sc,h,q}^{dis}$ <0.15P_{max}^{BESS} [-]
σ_P	Unit droop [-]

Variables	
$p^{band_{prim}}$	Daily primary reserve power band [MW] ≥0
$p^{band_{sec}}$	Daily secondary reserve power band [MW] ≥0
$p^{band_{sec_{DW}}}$	Daily downward secondary reserve power band [MW]
$p^{band_{sec_{UP}}}$	Daily upward secondary reserve power band [MW]
$p_{sc,h,q}^{BESS_{ABS}}$	Absolute power processed by the battery [MW] ≥0
$p_{sc,h,q}^{cha}$	Charging power [MW] ≥0
$p_{sc,h,q}^{cha_{a15}}$	Charging power > 0.15P_{max}^{BESS} [MW] ≥0
$p_{sc,h,q}^{cha_{b15}}$	Charging power < 0.15P_{max}^{BESS} [MW] ≥0
$p_{sc,h,q}^{dis}$	Discharging power [MW] ≥0
$p_{sc,h,q}^{dis_{a15}}$	Discharging power > 0.15P_{max}^{BESS} [MW] ≥0
$p_{sc,h,q}^{dis_{b15}}$	Discharging power < 0.15P_{max}^{BESS} [MW] ≥0
$p_{h,q}^{prim_{DW}}$	Downward primary reserve power flux [MW] ≥0
$p_{h,q}^{prim_{UP}}$	Upward primary reserve power flux [MW] ≥0
p_h^{purch}	Purchasing power DAM [MW] ≥0
$p_{h,q}^{purch_{qrt}}$	Quarter-of-hour component of p_h^{purch} [MW] ≥0
$p_{h,q}^{sec_{DW}}$	Downward secondary reserve power flux [MW] ≥0
$p_{h,q}^{sec_{UP}}$	Upward secondary reserve power flux [MW] ≥0
p_h^{sold}	Selling power DAM [MW] ≥0
$p_{h,q}^{sold_{qrt}}$	Quarter-of-hour component of p_h^{sold} [MW] ≥0
$p_h^{ter_{DW}}$	Downward tertiary reserve power offer [MW] ≥0
$p_{h,q}^{ter_{DW_{qrt}}}$	Quarter-of-hour component of $p_h^{ter_{DW}}$ [MW] ≥0
$p_h^{ter_{UP}}$	Upward tertiary reserve power offer [MW]≥0
$p_{h,q}^{ter_{UP_{qrt}}}$	Quarter-of-hour component of $p_h^{ter_{UP}}$ [MW] ≥0
$soc_{sc,h,q}^{BESS}$	State Of Charge [%] (within 0% and 100%)
$soc_{sc,(h,q)_{pre}}^{BESS}$	State Of Charge previous instant of time [%] (within 0% and 100%)
$y_{sc,h,q}^{BESS}$	Binary variable defining if the battery is used (=1 if ON, =0 if OFF) [-]
$y_{sc,h,q}^{cha}, y_{sc,h,q}^{dis}$	Binary variables defining if the battery is charging or discharging [-]
$y_{sc,h,q}^{cha_{a15}}, y_{sc,h,q}^{cha_{b15}}$	Binary variables defining the charging efficiency if $y_{h,q}^{cha} = 1$ [-]
$y_{sc,h,q}^{dis_{a15}}, y_{sc,h,q}^{dis_{b15}}$	Binary variables defining the discharging efficiency if $y_{h,q}^{dis} = 1$ [-]
y_h^{purch}, y_h^{sold}	Binary variables defining the 'direction' of DAM hourly commercial position [-]
$y_{h,q}^{purch_{qrt}}, y_{h,q}^{sold_{qrt}}$	Binary variables defining the 'direction' of DAM quarter-of-hour power flux [-]
$y_h^{ter_{UP}}, y_h^{ter_{DW}}$	Binary variables defining the 'direction' of tertiary hourly commercial position [-]
$y_{h,q}^{ter_{UP_{qrt}}}, y_{h,q}^{ter_{DW_{qrt}}}$	Binary variables defining the 'direction' of tertiary quarter-of-hour power flux [-]

APPENDIX B: ADDITIONAL EQUATIONS

Tmin^{ter} constraints:

$$p_h^{ter_{UP}} * Tmin^{ter} + \sum_{hh=h}^{t_{end}} \left(\frac{\sum_{q=1}^{4} \left(p_{hh,q}^{prim_{UP}} - p_{hh,q}^{prim_{DW}} + p_{hh,q}^{sec_{UP}} - p_{hh,q}^{sec_{DW}}\right)}{4} + p_{hh}^{sold} - p_{hh}^{purch} \right) \le \frac{soc_{sc,h,1}^{BESS}}{100} * E^{BESS} * \eta^{dis_{a15}}$$

$$p_h^{ter_{DW}} * Tmin^{ter} + \sum_{hh=h}^{t_{end}} \left(\frac{\sum_{q=1}^{4} \left(-p_{hh,q}^{prim_{UP}} + p_{hh,q}^{prim_{DW}} - p_{hh,q}^{sec_{UP}} + p_{hh,q}^{sec_{DW}}\right)}{4} - p_{hh}^{sold} + p_{hh}^{purch} \right) \le \frac{100 - soc_{sc,h,1}^{BESS}}{100} * \frac{E^{BESS}}{\eta^{cha_{a15}}}$$

"Modified" model aFRR power fluxes:

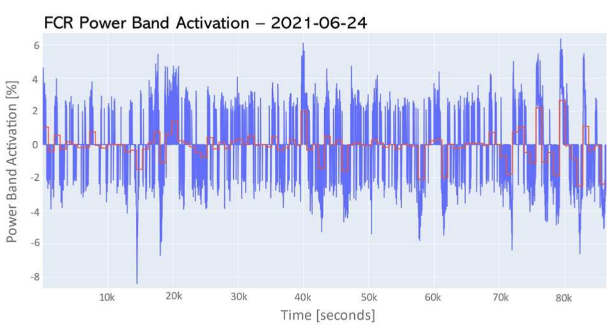
$$p_{h,q}^{sec_{UP}} = \frac{PERC_{h,q}^{sec}}{100} * p^{band_{sec_{UP}}} * Y_{h,q}^{sec_{UP}}$$

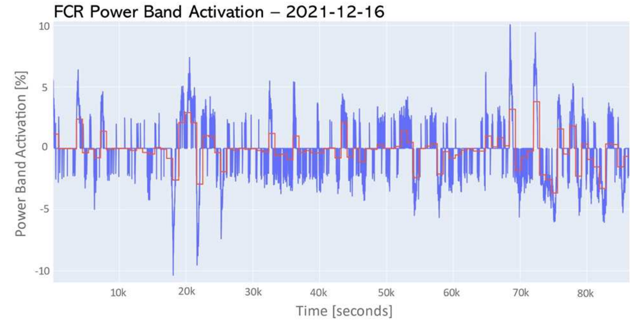
$$p_{h,q}^{sec_{DW}} = \left| \frac{PERC_{h,q}^{sec}}{100} \right| * p^{band_{sec_{DW}}} * Y_{h,q}^{sec_{DW}}$$

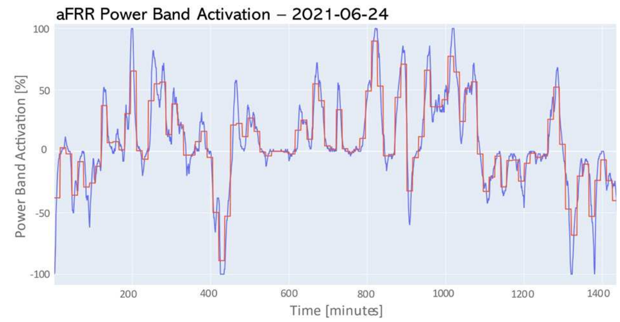
"Modified" model objective function:

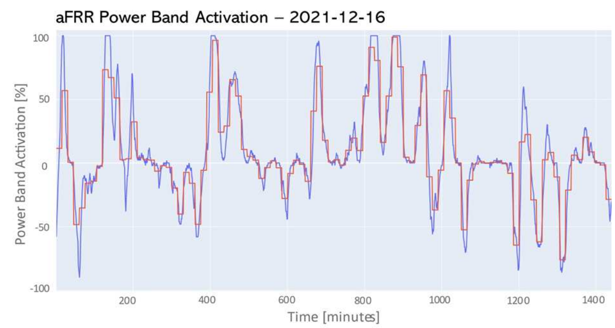
$$\begin{aligned}
\sum_{sc=1}^{6} P_{sc}^{scenario} * \sum_{h=1}^{24} \Big(& p_h^{ter_{UP}} * Y_{sc,h}^{ter_{UP_{par}}} * OFFER_h^{ter_{UP}} - p_{h,q}^{ter_{DW}} * Y_{sc,h}^{ter_{DW_{par}}} \\
& * OFFER_h^{ter_{DW}} \Big) \\
& + \sum_{h=1}^{24} \sum_{q=1}^{4} \left(\frac{p_{h,q}^{prim_{UP}}}{4} * PRICE_h^{prim_{UP}} - \frac{p_{h,q}^{prim_{DW}}}{4} \right. \\
& \left. * PRICE_h^{prim_{DW}} \right) + \sum_{h=1}^{24} PRICE_h^{cap_{prim}} * P^{band_{prim}} \\
& + \sum_{h=1}^{24} \sum_{q=1}^{4} \left(\frac{p_{h,q}^{sec_{UP}}}{4} * PRICE_h^{sec_{UP}} - \frac{p_{h,q}^{sec_{DW}}}{4} \right. \\
& \left. * PRICE_h^{sec_{DW}} \right) + \sum_{h=1}^{24} PRICE_h^{cap_{sec_{UP}}} * P^{band_{sec_{UP}}} \\
& + \sum_{h=1}^{24} PRICE_h^{cap_{sec_{DW}}} * P^{band_{sec_{DW}}} \\
& + \sum_{h=1}^{24} \left(p_h^{sold} - p_h^{purch}\right) * PRICE_h^{DAM} \\
& + \sum_{sc=1}^{6} P_{sc}^{scenario} * \frac{\left(soc_{sc,24,4}^{BESS} - 50\right)}{100} * E^{BESS} \\
& * PRICE^{DAM_{REF}}
\end{aligned}$$

APPENDIX C: FIGURES

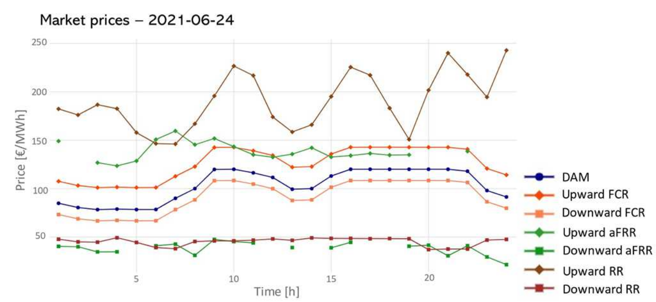


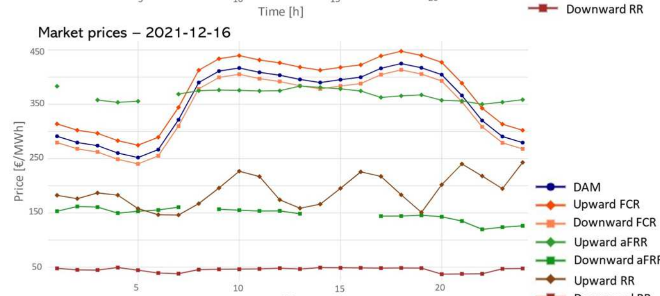


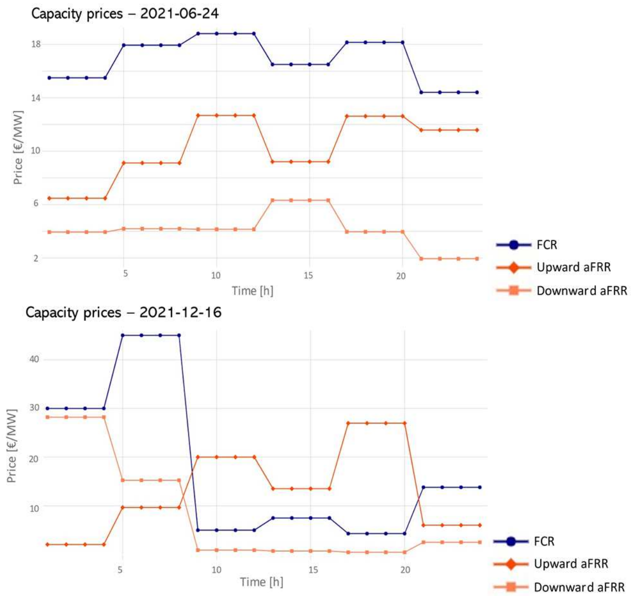




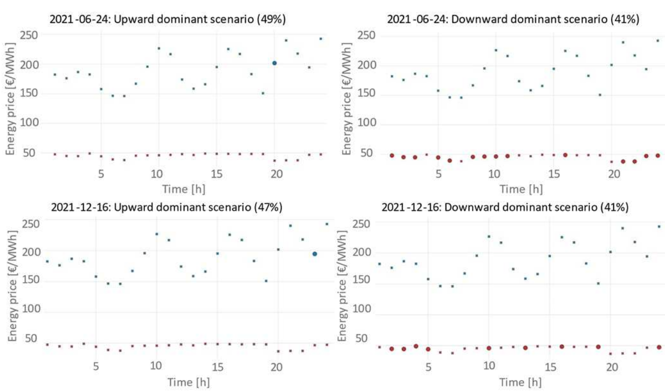
Appendix Figure 1 – FCR and aFRR activation profiles on the two typical days



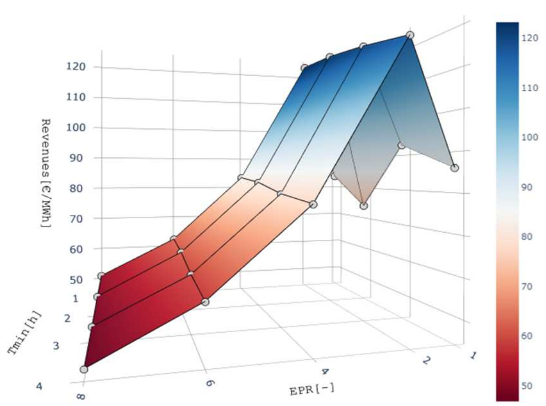




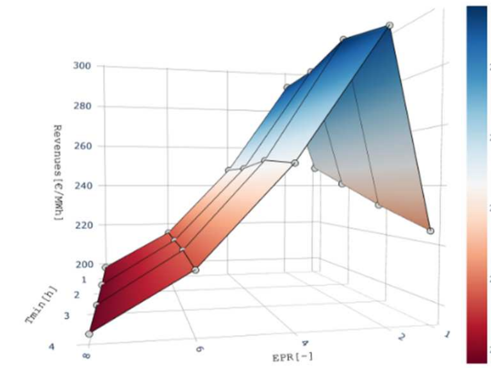
Appendix Figure 2- Market prices on the two typical days



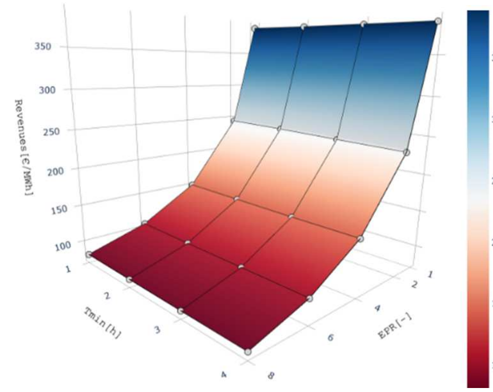
Appendix Figure 3 – Tertiary reserve scenarios on the two typical days



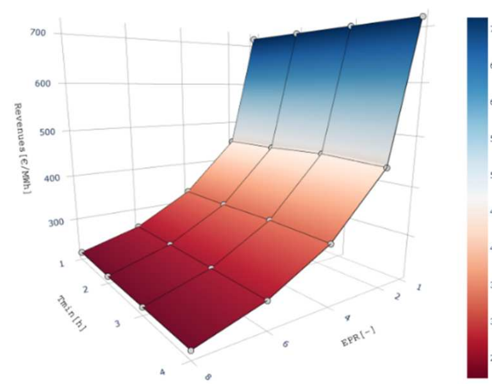
Appendix Figure 4 – Specific Revenues: "Basic" 2021-06-24



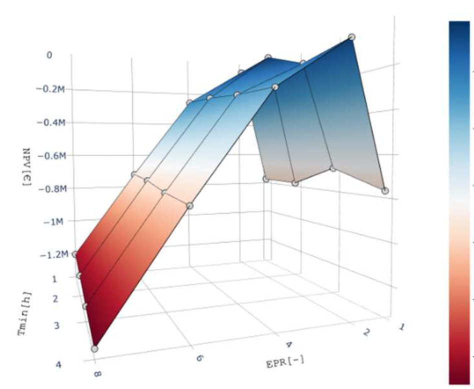
Appendix Figure 5 - Specific Revenues: "Basic" 2021-12-16



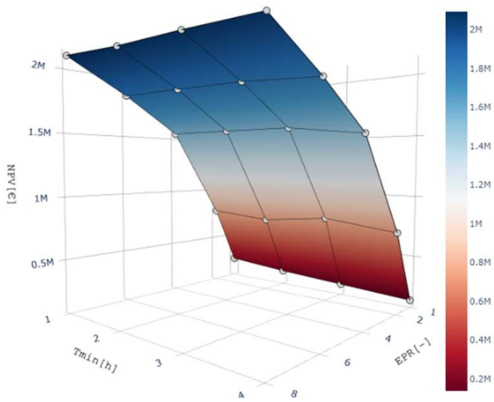
Appendix Figure 6 - Specific Revenues: "Modified" 2021-06-24



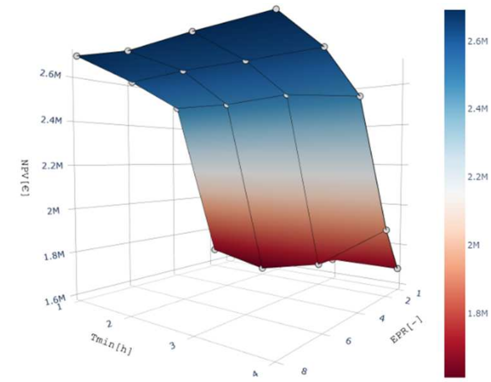
Appendix Figure 7 - Specific Revenues: "Modified" 2021-12-16



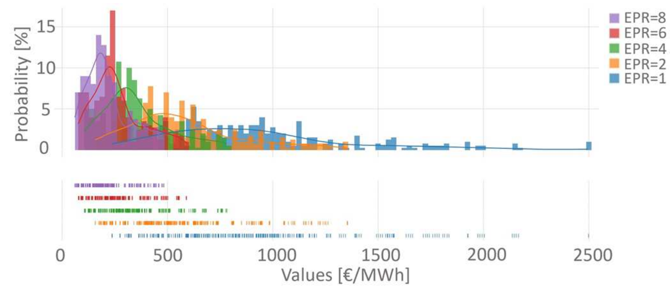
Appendix Figure 8 – NPV: "Basic" 2021-06-24



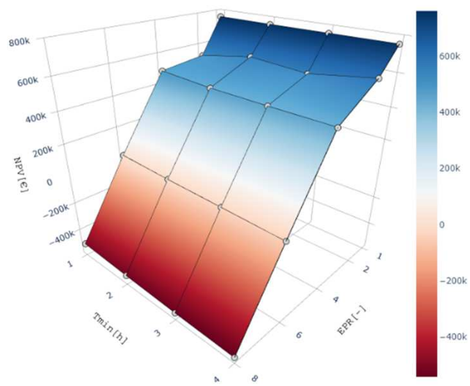
Appendix Figure 9 – NPV: “Basic” 2021-12-16



Appendix Figure 11 – NPV: “Modified” 2021-12-16



Appendix Figure 12 – Specific Revenues: “Modified” probability distributions for different EPR values



Appendix Figure 10 – NPV: “Modified” 2021-06-24