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Valuation of markets for small-to-medium scale flexibility management solutions in various power market regimes

Master Thesis
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Chapter 1

Introduction

1.1 Background

Background

Definition of flexibility

The challenges due to renewable penetration:

Traditional flexiblity from supply-side has limitations due to

The increasing demand can be fulfilled in various means, including conventional methods like generation (gas turbine), tramsimission (grid extend), which normally requires vast investments on infrastructure. With the develop of technologies in ICT and batteries, new options are becoming increasingly feasbile

The push and pull from market demands and technology availability is leading the policy makers to review or even revise the regulatory framework which were established based on the to allow non-discriminary participations of those new technologies.

Uncapping the potential

1.2 Technologies: options for system flexibility provision

- supply-side flexibility

  Conventional power plant response

  Curtailment of variable renewable

- Energy Storage System (ESS)

  Battery Energy Storage System (BESS)

  Pumped Hydro Energy Storage (PHES)

  Compressed Air Energy Storage (CAES)

Flywheel

- Demand Response (DR)
- Other

Electric Vehicle to Grid (V2G)

Electricity to Heat (E2H)

Power to Gas (P2G) / Power to Hydrogen (P2H)

1.3 Applications, benefits and business models

1.3.1 In liberalized market

Needs of different plyaers

Player * Market * Application

Energy Markets

Ancillary Service Markets

1.3.2 In vertically integrated market

1.4 Scope and research questions

The target audience of this thesis is the management at Landis+Gyr on a high coporate level.

The ultimate goal is to provide references to support the audiences' strategic decision makings regarding flexibility management.

In order to achieve this, we conducted qualitative studies and developed quantitative models to identify: 1) the value of markets for flexiblity management

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The goal of this thesis is to:

developed a robust modeling tool with moderate complexity so that it can not only provide results in current environment but can be also reused or easily revised to provide results in case of changes in the future.

based on the tool, make quantitative as well as quanlitative analysis to provide refer

Purpose: providing references for strategic decision makings regarding flexibility management.

In order to make the analysis robust and reliable, we have built a techno-economic models which include the bottom-up dynamics of some key elements regarding the electricity markets and flexilibity technologies.

However, it shall be noticed this thesis is not intended to serve for:

project developers to design a flexiblity system or make operating (including bidding) strategies of the system

policy makers to redesign the electricity market structure, rules or other policies

grid planners to understand the needs and options of flexibility in order to acheive system relability with lowest costs

Since the concept of flexiblity management is related to a great variety of technologies, applications and Landis+Gyr is positioning globally in various markets, the scope could be very broad. Nonetheless, in order to produce viable and reliable results with a solidily established techno-economic model, we have to make comprises. According to the relevance to Landis+Gyr's business, the scopes are defined as:

The potential business model of Landis+Gyr is either to supply products to the customers to help them enable flexibility or to directly sell them flexible MWs as a service. In this case, we want to understand the value of each MW we enabled or sold. We assume Landis+Gyr will not directly partipate and trade in the power market, as it is going to place Landis+Gyr at the rival side of some customers in that market.

The value of flexibility will definitely vary according to the purpose, users' portfolio and operating strategies.

Chapter 2

Literature Review

As is clearly revealed by the literuare review, there exist abused research articles generally on this topics of flexibility management. However, there exist very few academic works that serves the needs of our target audiences who are the management of technology vendors. The deviationsof interests result in gaps that make it difficult to directly use the existing works. These gaps include:

- Most of the researches are based on one specific technology and one specific market, as usually a utility company or a grid planner is operating in one market regimes and a technical professional is focusing on one technology. However, our target audiences are likely to be interested in various markets and technologies.

- Scope

- Mothed - proof of concept

Conventionally, their decision makings are supported primarily by commercial consulting firms who relied much on qualitative anlysis or quantitative data-anlytics. Even when sometimes it is possible that those firms have developed model with fundamental and physical approach, the model is always customized and not public

most of the researches are focusing one specific technology and one specific market, due to the nature of their target audiences. However, the managment iof a technology vendor will likely to be interested in various markets and various technologies.

The economics of flexibility solutions in power systems, especially electric energy storage (EES), is an active topic in research. It has drawn great attentions from the academics, investors and policy makers.

2.1 Purpose and stakeholder

2.2 Modelling methodology

2.2.1 Overview

Engineering vs system Linear vs nonlinear Deterministic vs stochastic problems Solving techniques

2.2.2 Engineering model

Price taker perfect forecast stochastic or dynamic programming Hybrid system Service mutualization

2.2.3 System model

2.3 Affecting factor

2.3.1 Techno-economic characteristics of power system

Generation

Generation mix (Renewable integration) Fuel Prices

Climate and weather

Transmission

Grid topology Transmission capacity

Consumption

Merit-order model

[1]

[2] [3] [4] [5] [6] [7] [8] [9] [10]

2.3.2 Statistic model

[11]

2.3.3 Perfect forecast

[12] [13] [14] [15] [16]

2.3.4 Power market degisn and policy regulation

Player and competitive landscape

Renewable Support Scheme

Power Market Design

Market structure and rules: nodal, interval, reserve market Access

In general, the seven ISOs/RTOs require companies that service loads (i.e., the energy re- quirements of end-use customers) to provide reserves in proportion to their loads. (ref to Project Report: A Survey of Operating Reserve Markets in U.S. ISO/RTO-managed Electric Energy Regions)

Balancing market design [17] [18]

Ownership and dispatch

Direct policy support

Capacity market Feed-in premium or tariff Other program

2.4 Value of results for reference

2.4.1 Demand for flexiblity in power system

2.4.2 Profitability of flexibility solutions

Chapter 3

Power Markets and The Role of Flexiblity Management

This chapter introduces some key concepts of power market elements and how the role of flexiblity management is determined by them. We adopted a generalized method to extract the key variances in power market structures that have impacts on value of flexiblity management. The purpose of this chapter is to provide the managment of a technology vendor who plan to expand their business in a variety of geographies a comprehensive and comparative view on flexiblity managment in different power market regimes.

3.1 Power market frameworks

Started in the 1980s and facilitated in 1990s, liberalized power markets has been the mainstream worldwide, especially in developed countries where the constructions of power infrastructure have been largely completed. [19] Nowadays, there are many maturely existing liberalized power markets. However, since different preconditions exists in different countries due to historical, political and climatical reasons, the structure of their power markets tend to be very heterogeneous. Moreover, with the development of technologies, for instance the renewable penetration and rise of demand response as well as electricity storage, power markets face pending or undergoing restructuring, make them a rapidly changing field of the economy. [20]

These spatial and temporal variances bring great challenges to our study as the business models of flexiblity managment and values out of them depend extensively on the power market structure. Hereby we reviewed and analyzed the existing mechanisms of how power makets can possibly enable the value creation of flexiblity management. Proposing novel market mechanisms is out of the scope of our study.

3.1.1 General stucture of power markets

3.1.2 Key attributes of power market stucture

3.2 Overview

Power exchange / Power pool
Capacity or not
Locational pricing or not

3.2.1 Energy market

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3.2.3 Capacity remuneartion mechanism

3.3 Power market design and structure

3.3.1 PJM

3.3.2 Germany

3.3.3 Australia

3.4 Regulatory and market framework for flexibility resourses

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Chapter 4

Methodology for Quantitative Valuation of Flexibility Management Markets

This chapter presents the methodologies of quantifying the value of flexibility managment markets. A modular approach is adopted to overcome the complexity from multi-dimensioning market-technology contexts. Firstly, the modules, categorized into market- and technology- based groups, are introduced. Then we will explain how these modules are to be organized with a optimization together with some special measures for certain cases.

4.1 Modular approach to build valuation models

As is reviewed in Chapter 2, in a typical academic work studying the value of flexibility, a model would be built with one specific environment, i.e. a market-technology context. In this thesis, however, a list of different markets and two different technologies are being studied, in order to better fulfill the needs of our targeted audience. The two dimensions of variables result in a significate number of cases of environment. It is not possible to generalize the model for these cases due to multi-dimensional structural differences. On the other hand, building a model for each case will lead to reduancy and make the model less usable and harder to be maintained in the future. Therefore, we adopt a modular approach where the dynamics of markets (or technologies) are generalized and varable in market-based (or technology-based) modules. The modular approach does not reduce the complexity of the problem, but just make the model more structurally organized.

Table 4.1 offers an overview of all the modules and their inputs and

Table 4.1: List of modules

Module name	**Input**	**Output**
Market-based modules		
Revenue module	Price signals (Determinate part), Frequency control singals, Sets of targeted marketplaces	Matrix of coefficients for revenue calculation
Risk module	Price signals (Distribution of stochastic part), Frequency control singals, Sets of targeted marketplaces	Matrix of coefficients for calucating Conditional Value-at-Risk
Market simulation module	Generation by fule type, consumption and its elasity	Price and volume signals
Market constraints	Volume signals	Constraints for optimization
Technology-based modules		
Cost module	Investment cost, Designed life time, Operating life time, System state	Matrix of coefficients for cost calculation
Technology simulation module	Efficiencies of charging, discharging and storing; Capacity; Energy-to-power ration	Matrix of coefficients to determine system states
Technology constraints	Historical data (Generation by fule type, consumption, market price and volume)	Price and volume signals

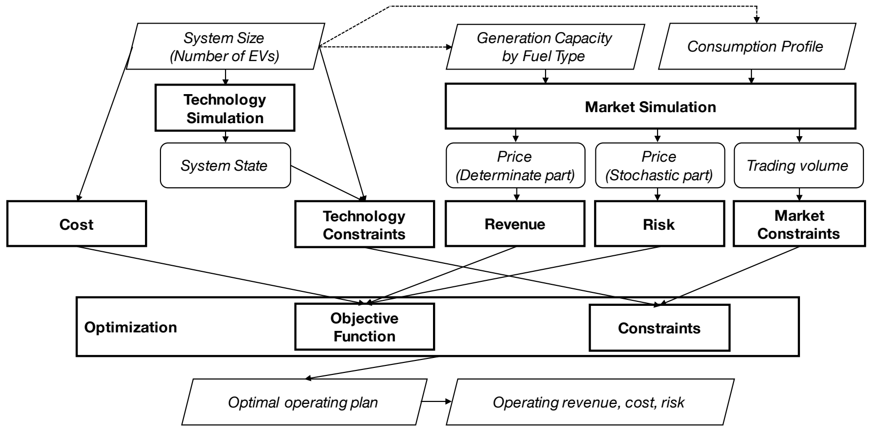

Figure 4.1: Flow chart of the techno-economic model

outputs. The working flow of the model is illustrated by Figure 4.1.

With this model, we can evaluate the profitability and risk associated with a certain size of flexibility management system in the power market and thus estimate the value of flexibility management market. Furthermore, the impacts of concerned factors including the renewable penetration, the cost reduction, and the possible diminishing return with increasing flexibility, etc. can be studied as well.

4.2 Market-based modules

4.2.1 Revenue module

In this study, we only account explicit revenues from power markets. At each time step ($t \in T$), the revenue is calculate as the amount of energy (e, in MWh) offered in each energy market segment ($i \in I$), and/or amount of reserve (r, in MW) offered in each reserve market segment ($j \in J$), mutiplied by their corresponding prices (π, in \$/MWh or \$/MW). In reserve market, there are additional revenues from energy provision while the committed capacities are activated. The amounts of energy delivered in reserve market are determined as a proportion to the committed reserve using a ratio (δ, in MWh/MW). Equation (4.1) illustrates how the overal revenue is determined.

$$Revenue = \sum_{t}^{t\in T} \left(\sum_{i}^{i\in I} \pi_t^{e,i}(e_t^{d,i} - e_t^{c,i}) + \sum_{j}^{j\in J} (\pi_t^{e,j}\delta_t^j + \pi_t^{r,j})r_t^j \right) \tag{4.1}$$

where, d and c in the superscripts denote "discharge" (to release energy from flexiblity resrouces to grids) and "charge" (to intake energy from girds to flexiblity resrouces) respectively. $e_t^{d,i}$, $e_t^{c,i}$, r_t^j, are endogenous varables of the whole model and decision variables of the optimization, which represent the operation plan of the flexibility resource in power markets.

I and J are sets of the selected market segments, and are determined according to the business case being studied. For example, we can set $I = \{Day\ ahead\}$ and $J = \emptyset$ in order to the value of making arbitrage in day-ahead energy market.

If there are multiple elements in $I \cup J$, it means the flexiblity resource can be reallocated to make offers to different market segments, i.e. performing multitasking. These cases need to be carefully coped with in avoidance of violating actual market rules. Detailed treatments regarding multitasking are illustrated in section 4.5.

The ratios δ are computed based on the real control signal when data is avaiable, or otherwise using system average ratios between total activated energy ($\hat{e}_t^{r,j}$) and the total reserve ($\hat{e}_t^{r,j}$) at each time step.

Price signals, $\pi_t^{e,i}$, $\pi_t^{r,j}$ and $\pi_t^{e,j}$, are inputs for the revenue module and may be retrieved either directly from the prepared datasets or from the outputs of market simulation module described in proceeding sections.

In order to better represent the state at each step over a period of time (T) and be implemented in optimizations, we re-formulate Equation (4.1) in form of vectors and matrices as following:

$$Revenue = \boldsymbol{f}\, X$$

where X is the vector for all desicion variables. For certain sets of market segments I and J, X can be derived using Equation (4.2) $\sim$ (4.5) with $i \in I$ and $j \in J$.

$$X = \begin{bmatrix} E^d \\ E^c \\ R \end{bmatrix} \tag{4.2}$$

$$E^d = \begin{bmatrix} E^{d,I(1)} \\ \vdots \\ E^{d,i} \\ \vdots \\ E^{d,I(|I|)} \end{bmatrix} E^{d,i} = \begin{bmatrix} e_1^{d,i} \\ e_2^{d,i} \\ \vdots \\ e_T^{d,i} \end{bmatrix} \tag{4.3}$$

$$E^c = \begin{bmatrix} E^{c,I(1)} \\ \vdots \\ E^{c,i} \\ \vdots \\ E^{c,I(|I|)} \end{bmatrix} E^{c,i} = \begin{bmatrix} e_1^{c,i} \\ e_2^{c,i} \\ \vdots \\ e_T^{c,i} \end{bmatrix} \tag{4.4}$$

$$R = \begin{bmatrix} R^{J(1)} \\ \vdots \\ R^{j} \\ \vdots \\ R^{J(|J|)} \end{bmatrix} \quad R^{j} = \begin{bmatrix} r_1^j \\ r_2^j \\ \vdots \\ r_T^j \end{bmatrix} \tag{4.5}$$

Function **f** can be obtained analogously using Eqution (4.6) $\sim$ (4.10) with $i \in I$ and $j \in J$.

$$\boldsymbol{f} = \left[\Pi^{e,I} \mid \quad -\Pi^{e,I} \mid \quad \Pi^{e,J}\Delta^{J} + \Pi^{r,J}\right] \tag{4.6}$$

$$\Pi^{e,I} = \left[\Pi^{e,I(1)} \mid \quad \dots \mid \quad \Pi^{e,I(|I|)}\right] \quad \Pi^{e,i} = \left[\pi_1^{e,i} \; \pi_2^{e,i} \; \dots \; \pi_T^{e,i}\right] \tag{4.7}$$

$$\Pi^{e,J} = \left[\Pi^{e,J(1)} \mid \quad \dots \mid \quad \Pi^{e,J(|J|)}\right] \quad \Pi^{e,j} = \left[\pi_1^{e,j} \; \pi_2^{e,j} \; \dots \; \pi_T^{e,j}\right] \tag{4.8}$$

$$\Pi^{r,J} = \left[\Pi^{r,J(1)} \mid \quad \dots \mid \quad \Pi^{r,J(|J|)}\right] \quad \Pi^{r,j} = \left[\pi_1^{r,j} \; \pi_2^{r,j} \; \dots \; \pi_T^{r,j}\right] \tag{4.9}$$

$$\Delta^{J} = diag(\delta_1^{J(1)}, \dots, \delta_T^{J(1)}, \dots, \delta_1^{J(|J|)}, \dots, \delta_T^{J(|J|)}) \tag{4.10}$$

4.2.2 Risk module

In accordance with the revenue calculation, we consider the uncertain movement of price as the primary source of risk. Referring to similar works that performed risk management for flexibility sources, e.g. EV2G [11] and DER [21], as well as for conventional energy trading companies [22], we developed a simple measure for risk control, by using the conditional value-at-risk (CVaR).

The CVaR (also named expected shortfall) as an extension of value-at-risk (VaR) can be defined as the difference between the expected profit and the average of potential profit values which are less than VaR [23], shown as:

$$CVaR_{\alpha}(X) = \int_{\alpha}^{1} VaR_s(X)ds \tag{4.11}$$

where α is the confidence level, and X is the underlying (the price of energy/ reserve in our study). The VaR, as the negative of α-quantile, can be computed as:

$$VaR_\alpha(X) = inf\{x \in \mathbb{R} \mid P(X + x < 0) \leq 1 - \alpha\} \tag{4.12}$$

Specially, in case the underlying variable subject to normal distribution, i.e. $X \sim \mathcal{N}(\mu, \sigma^2)$, we can derive the CVaR as:

$$CVaR_\alpha(X) = \mu - \sigma \frac{\phi(\Phi^{-1}(\alpha))}{1 - \alpha} \tag{4.13}$$

where, $\Phi(\cdot)$ is cumulative distribution function and $\phi(\cdot)$ is the probability density function of normal distribution.

Alternatively, if the uncertainties are dealt with in a discrete manner, the CVaR can be calculated as[23]:

$$CVaR_\alpha(X) = \underset{\zeta}{max} \left(\zeta - \frac{1}{1 - \alpha} \sum_s P(X, s)(\zeta - f(X, s)) \right) \tag{4.14}$$

where, $P(X, s)$ is the probability distribution function of X in the scenario s and $f(X, s)$ is the profit function in the scenario s. ζ is an auxiliary variable constrained by

$$\zeta - f(X, s) \leq \zeta_s$$
$$\zeta_s \geq 0$$

In our study, price terms $\tilde{\pi}$ are assumed to comprise a determinate part π and an independent stochastic deviation ϵ:

$$\tilde{\pi_t} = \pi_t + \epsilon_t \tag{4.15}$$

Since the stochastic terms ϵ are assumed to be incorrelated to each other, the CVaR of our portfolio that is built by $X^T = [E^d \mid E^c \mid R]$ in Equation (4.2) can be aggregated as:

$$\begin{aligned} CVaR = \sum_t^{t \in T} \{ & \\ & \sum_i^{i \in I} CVaR(\tilde{\pi_t}^{e,i})(e_t^{d,i} - e_t^{c,i}) \\ & + \sum_j^{j \in J} \left(CVaR(\tilde{\pi_t}^{e,j})\delta_t^j + CVaR(\tilde{\pi_t}^{r,j}) \right) r_t^j \\ & \} \end{aligned} \tag{4.16}$$

Analogous to the formation in preceding section, the risk module is also formated in vector and matix form.

$$CVaR = \boldsymbol{f} \begin{bmatrix} E^d \\ E^c \\ R \end{bmatrix}$$

where $\boldsymbol{f}$ is calculated as:

$$\boldsymbol{f} = \begin{bmatrix} CVaR(\Pi^{e,I}) \\ -CVaR(\Pi^{e,I}) \\ CVaR(\Pi^{e,J})\Delta^J + CVaR(\Pi^{r,J}) \end{bmatrix}^T \tag{4.17}$$

4.2.3 Market simulation module

As has been illustrated in the literature review (Chapter 2), valuation of flexiblity with a dynamic market condition is still a challenging task. While investment desicions are extensively concerned with long-term trends, profitability of arbitrage sensitively depends on short-term price movement in high resolution. This is distinguishing from conventional electricity generators for whom a long-term forecast with coase resultion is sufficient, and visual arbitrageurs who have almost no investments on infrastructures and may perform desicion-makings with a short-term perspective. A holistic approach combining these researches were taken sometimes [24][25] but may easily bring in unncessary complexity and lead to an overwhelming demand of resources, which are not essential for our study.

Therefore, in this thesis, we customized a market model based on existing researches by re-focusing on factors that are most relevant to our research questions, and simplying many other aspects of the power system and markets. Our market model is generally a statistic model built on observations of historical data, but a physical submodel is incorporated as well to study the impacts of some relevant variables whose features are not well captured by empirical observations.

The approach for market simulation differentiates between energy markets and reserve markets.

The energy markets are usually mature and with abundant degree of competition, so that we can employ an idealistic market model where the price formation is governed by the short run marginal costs (SRMCs) [26] [27]. This allows us to leverage a merit-order model to simulate the price levels, which are widely adopted as is summarized in Chatper 2.

The design of reserve markets, on the contrary, is not as straightforward as energy markets, which pose challenges for robust modeling. Besides, the market mechanisms vary spatially and temporally as is analyzed previously. Therefore, we adopt a pure statistic model for reserve market without involving any physical modeling.

Day-ahead energy market

The simulation for day-ahead energy market is preliminarily based on work done by [27] where the merit-order curve at supply shortage and surplus is modeled by an uplift effect. We further extend this work to capture the limits of flexiblity provision in current energy markets so that we can simulate the market conditions when the flexiblity become a challenge with growing renewables and/ or the flexibility becomes ubiquitous.

In [27], the peak price during periods of high demand is explained as fewer participants remain with spare generating capacity, putting these actors in a stronger bidding position to mark up the price. In constrast, when demand is low and plants with high SRMCs would not operate so further reduction in generation would favor plants with low SRMCs and thus reverse the bidding position. In both cases, the less available capacity remains, the stronger bidding position for the remaining players, which happens at the two end of merit-order cuve where the prices are driven up or down to significantly depart from the marginal cost. The symmetric effect is model with a uplift function:

$$U_t^g = 1 + \kappa \; e^{-\alpha\left(\frac{C_t^g - P_t^g}{C^g}\right)} \tag{4.18}$$

where g denote the class of generation in merit order, e.g. peak, flexible, inflexible, etc. (κ) and (α) are the parameters which can be obtained empirically [28]. In case of peak period, C_t^g represents total avaiable generation capacity of class g and P_t^g is the output of genertion of class g. During period of generation surplus, C_t^g is the remaining generation capacity while P_t^g is the curtailment required.

The middle of merit order curve can be modeled with a linear relationship.

Since the SRMCs of renewable generations are almost zero or even negative when they are remunerated by renewable support schemes, their position in power market is distinguishing from other generation players. Therefore, we employed the residual load, i.e. the load net of renewable generation, which has been introduced previously. We denote the residual load as $L^{res.}$ here.

According to the discussion above, the uplifts will occur when $L^{res.}$ exceeds the capacity of mid-merit generations and when $L^{res.}$ is smaller than operating capacity of inflexible generations.

Therefore, the merit order model for price formation can be formulated as:

$$\pi_t = \begin{cases} \dot{\pi}_t \left[1 + \kappa \ e^{-\alpha \left(\frac{C_t^g - P_t^g}{C^g} \right)} \right] & L_t^{res.} \leq C_t^{inflex.} \\ \dot{\pi}_t \ \kappa \ \frac{P_t^g}{C_t^g} & C_t^{inflex.} < L_t^{res.} < C_t^{inflex.} + C_t^{mid.} \\ \dot{\pi}_t \left[1 + \kappa \ e^{-\alpha \left(\frac{C_t^g - P_t^g}{C^g} \right)} \right] & L_t^{res.} \geq C_t^{inflex.} + C_t^{mid.} \end{cases} \tag{4.19}$$

In order to derive the value of generation capacity of each class, an invesigation into the flexiblity of power plants is necessary.

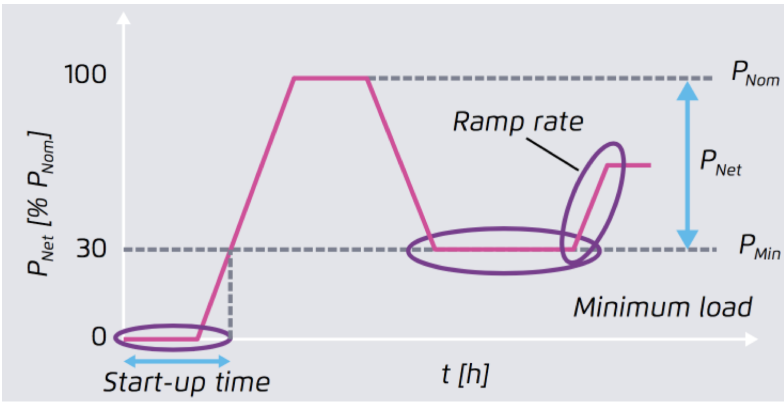

Figure 4.2: Qualitative representation of key flexibility parameters of a power plant[29]

The flexibility of a power plant can be characterised by three key features[29] (Figure 4.2.3):

- Overall bandwidth of operation: the range of output between minimum and maximum load;
- Ramp rate: the speed of adjusting output;
- Start-up time: the time required to attain stable operation from standstill

If a power plant can adjust its load from zero to nominate capacity within a time block in the day-ahead market (typically 1 hour), it can be deemed with infinite flexibility in the day-ahead market. This applies to most type generations including solar, wind, hydro and electrochemical systems, etc., except for generations using steam turbines [29], including nuclear, coal-, oil and gas-steam, etc. The gas turbines can be ramped up to full capacity within typicall 30 minutes[30][31]) so can be considered as flexible generation.

For a steam-turbine power plant, the minimun operational load is about 25-60% of its nominal capcity while the time required to start from standstill is longer than 2 hours [29]. Therefore, they are treated as limited flexible sources.

For limited flexible generations, an empirical analysis is performed to determine its bounded flexibility. The precedure for a certain generation source is decribed as following and shown as Figure 4.2.3:

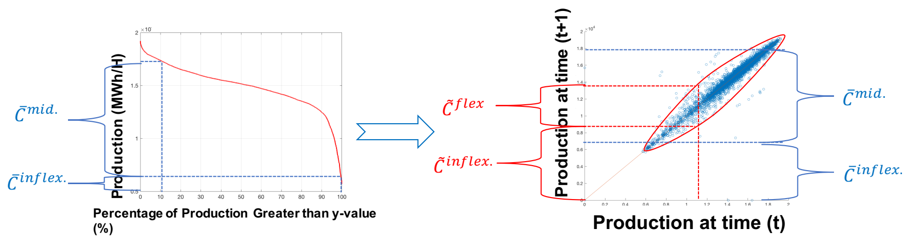

Figure 4.3: Schematic illustration of determining bounded flexibility for limited flexible generations

1. Make the duration curve of the generation data, and obtain $\bar{c}^{mid.}$ which is the range that the generation source is operating for over 10-99% of the overall period and $\bar{c}^{inflex.}$ which is the range that the generation is operating of more than 99% of the time

2. Determine the envolop lines which limit the production at time $t+1$ based on production at time t. With a certain production p_t, p_t is bounded within $\tilde{c}^{flex}$, and there is a range of production $\tilde{c}^{inflex}$ that is not economically viable to be curtailed.

3. Finnally, we find the relationship that map the production at time t to flexible capacity at time $t+1$ as:

$$\begin{aligned} c_{t+1}^{inflex.} &= \mathcal{C}^{inflex}(p_t) \\ &= max\{\tilde{c}_t^{inflex.},\ \bar{c}^{inflex.}\} \end{aligned} \tag{4.20}$$

and

$$\begin{aligned} c_{t+1}^{flex.} &= \mathcal{C}^{flex.}(P_t) \\ &= min\{\tilde{c}_t^{flex.} + \tilde{c}_t^{inflex.},\ \overline{c}^{mid.} + \overline{c}_t^{flex}\} - \tilde{c}_t^{inflex.} \end{aligned} \tag{4.21}$$

When the load exceeds the flexible range of these sources, they are no long able to participate in the bidding so these portion of capacity shall be deducted from the overall capacity for the calculation using Equation (4.19).

Finally, a regression is performed to determine the parameters in Equation (4.19) using empirical observations. The errors between a regressed value π_t and an actual value $\tilde{\pi}_t$ would be analyzed as the uncertanty of price movement and used for risk controlling as is discussed in risk module.

With a established merit-order model for day-ahead energy market, we can re-simulate the price with changed market condition, e.g. altered generation capacity mix.

Real-time energy market and reserve market

In electricity markets, large portion of energy is usually traded in day-ahead market [32]. There are significate dependences of the real-time (intraday, balancing) energy price on day-ahead price [7]. Therefore, for real-time energy prices, we adopt a simplex empirical analysis based on comparing the results from day-ahead price simulation and actual market data:

$$\pi_t^{RT} = \kappa(\pi_t^{DA} + \alpha) + \epsilon_t \tag{4.22}$$

where, κ and α are terms to adjust the determinate bias between day-ahead and real-time price, while ϵ_t represents the stochastic movement of real-time price.

For reserve market, only an empirical model is used as is discussed previously.

4.2.4 Market constraints

The market constraints are a list of limits to make sure that the operation of flexiblity resource (determined by X in Equation (4.2)) would not violate the actual market rules and market conditions.

Generally, these constraints can be formulated as

$$\begin{bmatrix}\Gamma^d & | & \Gamma^c & | & \Gamma^r\end{bmatrix} X \leq \boldsymbol{b} \tag{4.23}$$

Most of the market constaints are derived from the market rules so will be introduced in case studies where specific markets are being studies.

4.3 Technology-based modules

4.3.1 Cost module

In this thesis, we categorize all costs into two groups: operation-independent and operation-dependent costs.

Operation-independent costs

The first group mainly including the initial capital outlay for purchasing the devices and systems, plus the fixed operating and maintenance (O&M) costs which include miscellaneous items such as the insurance, employee salaries, etc.

The initial capital cost for a storage system can be divided into two components: an energy-based component, approximately linear to the energy capacity of the system (denoted $\overline{s}$, in MWh), and a power-based component, approximately linear to the power rate of the system (denoted $\overline{r}$, in MW) [33]. Additionally, we add a component representing the size-invariant costs such as the cost for software. Thereby, the initial capital cost can be computed as:

$$C^{ini} = C^s\overline{s} + C^r\overline{r} + C^0 \tag{4.24}$$

where, the coefficients can be obtained empirically either by screening actual market data or from literature. In addition, since the system cost for battery storage is falling rapidly, a learning rate of *ca.* 14% per annum can be taken to build future scenarios[34].

The initial capital cost is then annualized by using the concept of equivalent annual cost (EAC):

$$C^{EAC} = \frac{C^{ini}}{\frac{1-\frac{1}{(1+r)^a}}{r}} \tag{4.25}$$

where r is the discount rate and a is the lifespan of the system in number of years.

The discount rate can be established from the Weighted Average Cost of Capital (WACC) which depends on the financial conditions of different players. A typical WACC in the United States is *ca.* 4-6% for a municipal utility, 7-8% for a regulated utility and over 10% for independent power producer[24]. In this study, a discount rate of 10% is taken unless otherwise stated.

For fixed O&M costs, $C^{fO\&M}$ which is difficult to calculate precisely, an assumption of 2% of the initial capital cost is taken, referring to [24]. The fixed O&M costs are added directly to the annualized capital cost to get the total fix costs (in \$/year):

$$C^{fix} = C^{EAC} + C^{fO\&M} \tag{4.26}$$

The annualized fix cost will finally be compared with the operating revenue calculated from other module to assess the profitability.

Operation-dependent costs

Operation-dependent costs primarily refer to the degradation costs, which is specially an issue for battery-based energy storage systems[35].

However, as has been reviewed and analyzed in [33], there exists no single degradation model that is widely accepted among the literature and applicable for all cases, due to the complexity of this problem. The reasons can be summarised as following:

- Modelling battery degradation itself is a complex engineering problem as it is affected by a list of physical parameters, including the DoD, SoC, charging/discharing rate, temperature.[35]
- The choice of degradation model affects the convex relaxation when degradation effects are included in an optimization problem, the model selection is driven by the requirements of mathematical realization. [33]

Degredation costs can be neglected while operating life time is longer than designed life time, which is generally valid for non-battery energy systems [36][37][38]. Some research works studying battery system also made the same assumption [39][40][13]. The breakeven point of operatoinal frequency where the degradation of battery storage system can be ignored was concluded to be less than 0.5-1.5 full-cycle equivalent energy thoroughput per day[33]. Nonetheless, it was also pointed out by [33] that while assuming degredation cost being zero, the operational planner would tend to operate the system more frequently, which would possibly in turn to violate assumption of zero-degredation.

Such a combined investment and operation problem is hard to be incorporated in an optimization, so in our study we first use a simple degradation cost model where the cost is linear to the *energy thoroughput* $|e^t|$ as a damping term in the optimization and examine it *ex-post*, i.e. if the actual operating life is not reached the degradation cost will be exempted from the final profit calculation. A linear relationship between the degradation and $|e^t|$ is a common techique used in researches for estimating battery degradation[39][41].

Denoting the damping factor for degradation as ζ, we can formulate the degradation damping as:

$$C_t^{degradation} = \zeta(\sum_{i}^{i\in I}(e_t^{d,i} + e_t^{c,i}) + \sum_{j}^{j\in J}(\delta_t^{j,+} + \delta_t^{j,-})r_t^j) \tag{4.27}$$

where, the energy to reserve ratios are separated to positive and negative components:

$$\delta_t^{j,+} = \begin{cases} \delta_t^j & \delta_t^j \geq 0 \\ 0 & \delta_t^j < 0 \end{cases} \tag{4.28}$$

$$\delta_t^{j,-} = \begin{cases} 0 & \delta_t^j \geq 0 \\ -\delta_t^j & \delta_t^j < 0 \end{cases} \tag{4.29}$$

It can be noticed that when a virtual arbitrage is conducted where some $e_t^{d,i}$ and $e_t^{c,i}$ are offset, it will activate the degradation damping with Equation (4.27) while there are no real physical processes causing degradation. This will be corrected in final profit calculation but in decision making process using optimizations we keep it as it is intended to restrict the virtual arbitrage.

Similar to Equation (4.10), we reconstruct the diagonal matrices with the decomposed ratios from Equation (4.28) and (4.29).

$$\Delta^+ = diag(\delta_1^{J(1),+}, \dots, \delta_T^{J(1),+}, \dots, \delta_1^{J(|J|),+}, \dots, \delta_T^{J(|J|),+}) \tag{4.30}$$

$$\Delta^- = diag(\delta_1^{J(1),-}, \dots, \delta_T^{J(1),-}, \dots, \delta_1^{J(|J|),-}, \dots, \delta_T^{J(|J|),-}) \tag{4.31}$$

The matrix of coefficient for degradation is the derived complying with the form of market modules:

$$Cost^{degradation} = \begin{bmatrix} Z^I \mid & Z^I \mid & \zeta(\Delta^+ + \Delta^-) \end{bmatrix} \begin{bmatrix} E^d \\ E^c \\ R \end{bmatrix}$$

where,

$$Z^I = \begin{bmatrix} Z^{I(1)} & \mid & \dots & \mid & Z^i & \mid & \dots & \mid & Z^{I(|I|)} \end{bmatrix} \quad Z^i = \zeta \cdot I_{T\times T} \quad \forall i \in I$$

$I_{T\times T}$ is a $(T \times T)$ identity matrix.

4.3.2 Technology simulation module

The technology simulation is applied to determine the state of the system, which would be used primarily for calibration of technology constraints but also for *ex-post* analysis.

Energy Storage

Regardless of the type of technology, an energy storage system consists of three functional units, i.e. power input, power output, and storage. Each function unit is associated with an efficiency, i.e. conversion efficiencies of charging, discharging and storage efficiency, denoted as η_c, η_d and η_s respectively.

Since the ramp up time for a typical storage system is neglectible comparing to the time resolution in our study, the state of power input and output are deemed as strictly following the operational plan without transient process.

For the state of storage, we define a term, s (in MWh), which is the energy stored in the device, i.e. the State-of-Charge (SoC) multiplied by its maximum energy capcity. The state is determined using Equation 4.32.

$$s_t = \eta_s s_{t-1} + \eta_c(\sum_i^{i\in I} e_t^{c,i} + \sum_j^{j\in J} \delta_t^{j,-} r_t^j) - \frac{1}{\eta_d}(\sum_i^{i\in I} e_t^{d,i} + \sum_j^{j\in J} \delta_t^{j,+} r_t^j) \tag{4.32}$$

In order to formulate Equation (4.32) in matrix form, we first introduce a matrix denoted H:

$$H = \begin{bmatrix} \eta_s^0 & 0 & 0 & \dots & 0 \\ \eta_s^1 & \eta_s^0 & 0 & \dots & 0 \\ \eta_s^2 & \eta_s^1 & \eta_s^0 & \dots & 0 \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ \eta_s^{T-1} & \eta_s^{T-2} & \eta_s^{T-3} & \dots & \eta_s^0 \end{bmatrix}$$

Then M is used to construct H^I and H^J with a given pair of sets of market segments I and J.

$$H^I = \begin{bmatrix} H^{I(1)} & | & \dots & | & H^i & | & \dots & | & H^{I(|I|)} \end{bmatrix} \quad H^i = H \quad \forall i \in I$$

$$H^J = \begin{bmatrix} H^{J(1)} & | & \dots & | & H^j & | & \dots & | & H^{J(|J|)} \end{bmatrix} \quad H^j = H \quad \forall j \in J$$

Finally, we can derive the matrix form of Equation (4.32).

$$S = \eta_s H S_0 + \begin{bmatrix} -\frac{1}{\eta_d} H^I & | & \eta_c H^I & | & H^J(-\frac{1}{\eta_d}\Delta^+ + \eta_c \Delta^-) \end{bmatrix} X \tag{4.33}$$

where, S and S_0 are vectors for the temporal and initial state, respectively.

$$S = \begin{bmatrix} s_1 & s_2 & \dots & s_T \end{bmatrix}^T$$

$$S_0 = \begin{bmatrix} s_0 & s_0 & \dots & s_0 \end{bmatrix}^T$$

In order to make it more compact, we reformulate Equation (4.33) as:

$$S = \boldsymbol{h}_0 + \boldsymbol{h}\ X \tag{4.34}$$

where

$$\boldsymbol{h}_0 = \eta_s H S_0 \tag{4.35}$$

$$\boldsymbol{h} = \left[-\tfrac{1}{\eta_d} H^I \quad | \quad \eta_c H^I \quad | \quad H^J(-\tfrac{1}{\eta_d}\Delta^+ + \eta_c \Delta^-) \right] \tag{4.36}$$

Electric Vehicle

Electric vehicle to grid systems are fundamentally battery energy storage systems in term of their physical dynamics. Therefore, they can be modeled generally using the same approach as in preceding paragraphs. However, there are several attributes that uniquely characterize electric vehicle to grid systems compared to normal battery storages:

- The availability of an EV2G system, in terms of delivering both energy (in MWh) and capacity reserve (in MW), is dynamic rather than static, since the number of EVs connected in the power grid is changing all the time with the behaviors of plug-in/ plug-out.
- The energy stored in the system will be consumed not only for delivering our targeted services (arbitrage or balancing), but also for driving of EVs themselves. This part of costs will be implicitly captured by the revenue module using Equation (4.1), which will distort the real value of services provided for the grid.

Therefore, two main modifications are made to adapt the model of ESSs for better representing the EV2G systems:

1. The EV2G system is modeled as a dynamic ESS by taking into consideration the connection/ disconnection of EVs to/ from the grids.
2. The costs of energy consumed for driving are accounted, following the original plan, i.e. without controlling algorithm for grid services, and added back to the revenue in Equation (4.1).

In order to implement the first measure, we introduce additional terms to represent the number of EVs entering (n_t^+), leaving (n_t^-) and remain in (n_t) the system at each time step.

$$n_t = n_{t-1} + n_t^+ - n_t^- \tag{4.37}$$

Thereby the state equation for an EV2G system is written as:

$$\begin{aligned} s_t =& \eta_s s_{t-1} + \eta_c(\sum_i^{i\in I} e_t^{c,i} + \sum_j^{j\in J} \delta_t^{j,-} r_t^j) - \frac{1}{\eta_d}(\sum_i^{i\in I} e_t^{d,i} + \sum_j^{j\in J} \delta_t^{j,+} r_t^j) \\ &+ s^+ n_t^+ - s^- n_t^- \end{aligned} \tag{4.38}$$

The matrix form of Equation (4.37) is as following:

$$N = I_{T\times T}N_0 + L_{T\times T}N^+ - L_{T\times T}N^- \tag{4.39}$$

where, $L_{T\times T}$ is a $(T\times T)$ identity lower triangular matrix. The rest matrices are defined as following

$$N = \begin{bmatrix} n_1 & n_2 & \dots & n_T \end{bmatrix}^T$$

$$N_0 = \begin{bmatrix} n_0 & n_0 & \dots & n_0 \end{bmatrix}^T$$

$$N^+ = \begin{bmatrix} n_1^+ & n_2^+ & \dots & n_T^+ \end{bmatrix}^T$$

$$N^+ = \begin{bmatrix} n_1^- & n_2^- & \dots & n_T^- \end{bmatrix}^T$$

Analogously, translating Equation (4.38) to matrix form leads to:

$$\begin{aligned} S = {} & \eta_s H S_0 + s^+ H N^+ - s^- H N^- \\ & + \left[-\tfrac{1}{\eta_d} H^I \;\middle|\; \eta_c H^I \;\middle|\; H^J(-\tfrac{1}{\eta_d}\Delta^+ + \eta_c \Delta^-) \right] X \end{aligned} \tag{4.40}$$

which can be reformulated as:

$$S = \boldsymbol{h}_0 + \boldsymbol{h}\, X \tag{4.41}$$

where

$$\boldsymbol{h}_0 = \eta_s H S_0 + s^+ H N^+ - s^- H N^- \tag{4.42}$$

$$\boldsymbol{h} = \left[-\tfrac{1}{\eta_d} H^I \;\middle|\; \eta_c H^I \;\middle|\; H^J(-\tfrac{1}{\eta_d}\Delta^+ + \eta_c \Delta^-) \right] \tag{4.43}$$

4.3.3 Technology constraints

The technology constraints are set to ensure the operation plan is fulfilled physically by the system.

Energy storage

Firstly, the chargning/ discharging rate shall be bounded at its maximum rate.

$$0 \le \frac{1}{\Delta t} \sum_{i}^{i\in I} (e_t^{d,i} - e_t^{c,i}) + \sum_{j}^{j\in J} r_t^j \le \overline{r} \quad \forall t \in T \tag{4.44}$$

Meanwhile, the energy stored is restricted as well.

$$0 \le s_t \le \overline{s} \quad \forall t \in T \tag{4.45}$$

Replacing s_t using Equation (4.32), the contraint is formulated as:

$$0 \le \eta_s s_{t-1} + \eta_c(\sum_{i}^{i\in I} e_t^{c,i} + \sum_{j}^{j\in J} \delta_t^{j,-} r_t^j) - \frac{1}{\eta_d}(\sum_{i}^{i\in I} e_t^{d,i} + \sum_{j}^{j\in J} \delta_t^{j,+} r_t^j) \le \overline{s} \tag{4.46}$$

Applying the matrix format of the equations, we can get the constraints re-formulated the constraints of rates as:

$$-\frac{1}{\Delta t}\left[\overbrace{I_{T\times T}|\dots|I_{T\times T}}^{|\mathrm{I}|}\,|\,\overbrace{-I_{T\times T}|\dots|-I_{T\times T}}^{|\mathrm{I}|}\,|\,\overbrace{I_{T\times T}|\dots|I_{T\times T}}^{|\mathrm{J}|}\,|\right] X \le 0 \tag{4.47}$$

$$\frac{1}{\Delta t}\left[\overbrace{I_{T\times T}|\dots|I_{T\times T}}^{|\mathrm{I}|}\,|\,\overbrace{-I_{T\times T}|\dots|-I_{T\times T}}^{|\mathrm{I}|}\,|\,\overbrace{I_{T\times T}|\dots|I_{T\times T}}^{|\mathrm{J}|}\,|\right] X \le \overline{R} \tag{4.48}$$

where,

$$\overline{R} = \left[\overbrace{\overline{r},\dots,\overline{r}}^{\mathrm{T}}\right]^T$$

And the constraints of storage are formulated as:

$$-\boldsymbol{h}\, X \le \boldsymbol{h}_0 \tag{4.49}$$

$$\boldsymbol{h}\, X \le \overline{S} - \boldsymbol{h}_0 \tag{4.50}$$

where, $\boldsymbol{h}$ and $\boldsymbol{h}_0$ are determined by Equation (4.34) to (4.36)

Electric vehicle to grid

The constraints for ESS are generally portable for the EV2G systems, by simplying re-using Equation (4.41) to (4.43) to derive $\boldsymbol{h}$ and $\boldsymbol{h}_0$, and replacing the upper bound limit in Equation 4.48 with

$$\overline{R} = \overline{r}N \tag{4.51}$$

where, N is determined by Equation (4.39).

4.4 Optimization Engine

The performance of a flexibility resource depends primarily on the operation plan, which is represented as X (Equation 4.2). In order to value the market of technology vendors supplying flexibility to actors in power markets, we need to find reasonal operation patterns that simulate the behaviors of those players. For this sake, we employ a optimization engine. The value of market calculated with the results from optimization stands for the upper bound of market value.

The objective function of the optimization problem is formulated as:

$$\underset{X}{max} \left[(1-\beta)\left(Revenue(X) - C^{degradation}(X)\right) - \beta CVaR(X)\right] \tag{4.52}$$

where, X is the vector of decision variables (Equation (4.2)), and $Revenue$, $C^{degradation}$ and $CVaR(X)$ are calculated using the equations in corresponding modules. β is a weighting parameter with $\beta \in [0,1]$, which is used to study the trade-off between profit and risk.

The constraints have been introduced in the modules of market and technology constraints.

The optimization is implemented in MATLAB© and solved using Guobi optimizer.

4.5 Addtional measures for speical cases

4.5.1 Backcast technique to reduce the predictability of price

As has been discussed in the literature review, many of the researches on arbitrage of flexibility in power markets assume the players have perfect foresights of future price movement, which would lead to an over-estimate of the real market value. Reducing the length of perdictable window, using 'backcast' technique, and introducing stochastic programming are the usual choices to deal with this issue.

In this thesis, although the players would suffer risks of uncertain price movement with the introduction of stochastic part of price, they were still assigned with full foresight of the probability distribution. One may argue this is also unrealistic and could probably over-estimate the market potential. Therefore, by extending the work [15] and [13], we preformed a sensitivity analysis with reduced predictability using backcast.

We assume the way players predict the short-term forecast of future price is using the following equation:

$$\hat{\pi}_t = \hat{\pi}_{t-t_w} \cdot \frac{\sum_{t-t_w+1}^{t-t_d} \pi_\tau}{\sum_{t-t_w-t_w+1}^{t-t_w-t_d} \pi_\tau} \tag{4.53}$$

where, t_w is the time period of one week and t_d is the time of one day. The future price is determined by taking the price curve shape of the day of last week and is adjusted by the 7-days average price level.

4.5.2 Coupling day-ahead and real-time energy market

When we value a case where player can participate in day-ahead and real-time (intraday, balancing) energy markets at the same time, an issue rises as they were assigned with full foresight and could easility leverage this advantage to make virtual arbitrage between day-ahead and real-time markets. Since the virtual arbitrage does not activate any physical process and purely benefited from the unrealistic foresight, it has to be constrained. Some researchers have also noticed this issue and used techniques such as put a proportional constraint of real-time volume to day-ahead volume [21] or deny reserved biddings between day-ahead and real-time market [41].

In this thesis, the virtual arbitrage has already been damped by the degradation model as has been discussed in Section 4.3.1. Furthermore, we would perform a two-stage optimization where the day-ahead decisions will be made without knowing the real-time prices and the decisions for real-time market biddings will be determined afterwards to reflect the real market condition. We will compare the impact of virtual arbitrage in sensitivity analysis.

4.5.3 Dealing with non-energy-neutral signal for frequency control

Providing frequency control is an attractive option for flexibility management as it is more profitable than energy arbitrage in current market context. However, a challenge of performing frequency control with non-generting flexibility sources is the non-energy-neutral signals of frequency regulation. If the control signal is not energy-neutral or not auto-corrected, it is not possible for a non-generting resource to provide servise for an extended period due to the limited energy capacity. For example, a battery cannot absorb any more energy while it is fully charged and fail to continue delivering frequency control services.

Altough some system operators have already implemented special energy neutral signals for the emerging flexibility resources, it is not a universal practise among the markets.

In this study, we referred to the similar works [33][42][43][44] where the biased regulation signals are offset using external measure, e.g. via bilateral transactions or pruchasing from the power markets. We assume that actors will purchase energy from the power market with real-time price to neutralize the regulation signal .

4.5.4 Final adjusted profit calculation

As has been discussed above, we have introduced a list of treatments to better model the problem. However, some of the treatments would distort the perceived profits deviating from actual profits received by the actors, i.e. the differences exist between the value for decision making and for final accounting. Therefore, after performing the optimization, we would use the determined operation plan to re-calculate the profits to get the real values.

(Descriptions about Data has been moved to the chapter of case study as they are market-specific rather than generic.)

Chapter 5

Case Studies

5.1 Analyzing the power market structures and business opportunities in select cases

The superset of I is the set of selected energy market segments in different geographies:

$$I \subseteq \begin{cases} \{Day\ Ahead, Real\ Time\} & PJM \\ \{Day\ Ahead, Intraday, Balancing\} & Germany \\ \{Real\ Time\} & NSW \end{cases}$$

The superset of I is the set of selected reserve market segments in different geographies:

$$J \subseteq \begin{cases} \{RegA, RegD, SR, NSR, DASR\} & PJM \\ \{PCR, SCR+, SCR-, TCR+, TCR-\} & Germany \\ \{Lower, Raise\} \times \{REG, 6SEC, 60SEC, 5MIN\} & NSW \end{cases}$$

5.1.1 PJM

Organization of PJM power markets

Marketplaces Timeline

Players

A Load Serving Entity (LSE), as is defined officially by PJM, is "any entity that has been granted authority or has an obligation pursuant to state or local law, regulation, or franchise to sell electric energy to end-users that are located within the PJM RTO. An LSE may be a Market Buyer or a Market Seller"[45]. Therefore, LSEs refer to all market participates in PJM who have rights and obiligation to act in all the power marketplaces of PJM, including the energy, capacity and ancillary services markets.

Curtailment Service Providers (CSPs) are members in PJM markets specializing in demand response. A CSP is an intermitted agency that provides the end-user DR to the wholesale market. [45] [46] The role of the CSP is actually a legacy product from the liberalization of retail markets in PJM. Once the retail competition began, PJM allowed LSEs to provide DR not only for their own customer but also for customers of other LSEs. The role of the CSP was created to facilitate the liberalization and competition. [47]

Balancing mechanism

submit offer - rebid - update information up to 65 mins - deviation charged with real-time

reviewed the participation, violating -> suspend activity, enter enforcement

LSE obiligate to purchase (or self-schedule) reserve, obiligation as a proportion to its contributing flow to the grid. [48] This incents liquidity in the market with competitions on both buyer's and seller's side. However, the obiligation does not reflect their actual needs.[17]

CSP intermitted agency allowed to voluntarily respond to the LMP

PJM DR

PJM DR is the umbrella for all distributed energy resources, including DR, behind-the-meter generations, storage, etc. since PJM does not specify how the load is reduced. However, PJM DR program does not allow energy injection beyond the meter and receive wholesale compensation.[47]. This issue is currently under discussion in Special Market Implementation Committee meetings.

DR emergency fast changing over years [49] Since the DR in the wholesale market as a supply recouse will cause double payment issue where a customer may receive wholesale energy revenue and retail cost savings for the same MW of load reduction, PJM states that DR participation in the retail market on the demand side would be more ideal. And they are discussing to revisit the mechanism. Therefore, this value is not fully modeled in our study.

LSE buyer or seller in Energy, and reserve market

Identify business model

Accounting

The real-time market price is applied for all deviations from day-ahead planned schedule, including Regulation, Primary and Supplementary Reserves.

$$\pi_t^{e,j} = \pi_t^{e,i} \quad i \in \{Real\ Time\}, j \in \{RegD, RegA, SR, NSR, DASR\}$$

The capacity prices of reserves are computed using a complex algorithm, taking into account a list of specifications of the resrouce, e.g. the performance & historical performance, benefits factor, milleage, etc. The detailed calculations can be found in appendix. As outputs, we will get deterministic values for $j \in \{RegA, SR, NSR, DASR\}$, and the upper and lower bounds, $\overline{\pi}_t^{r,j}$ and $\underline{\pi}_t^{r,j}$, for $i \in \{RegD\}$.

5.1.2 Germany

$\pi_t^{e,i}, i \in \{Balancing\}$, is the the price for balancing energy (reBAP), which exist only in Germany

$\pi_t^{r,j}$ and $\pi_t^{e,j}$ are based on principle of pay-as-bid. The weighted-average values are available in the datasets.

Prices for balacning energy are unified across TSOs and determined according to the balancing energy price settlement system (BK6-12-024) developed by Federal Network Agency (FNA) as of 01/12/2012.

$$reBAP = \frac{\sum netimbalanceenergycost}{\sum netimbalanceenergyvolume} \tag{5.1}$$

5.1.3 Australia-New South Walse

The unit prices of reserve products, $\pi_t^{r,j}$ and $\pi_t^{e,j}$, are not available in datasets published by AEMO. Only weekly summary for total payment and recovery are provided. Due to the limits of available data, we are only able to perform calculations of total potential revenues, rather than thorough studies as in the other two geopraphies.

5.2 Accounting rules and data preparation

5.3 Results and discussion

Chapter 6

Conclusions and outlook

Appendix A

Model parameters

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