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Power
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Laboratory

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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

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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

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2.3 Affecting factor

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Generation

Generation mix (Renewable integration) Fuel Prices

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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]

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

2.3.4 Power market degisn and policy regulation

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Power Market Design

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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

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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

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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 methodology for quantifying the value of flexibility managment markets. A modular approach is adopted to overcome the complexity from multi-dimensional market-technology contexts. Firstly, the modules are introduced, being categorized into market- and technology- based groups. Then we will explain how these modules are to be organized within a optimization.

4.1 Modular approach to build valuation models

In this thesis, a list of different markets and two different technologies are being studied. This results 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 redudancy and make the model less usable and harder to maintain. 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 renders the model more structurally organized.

Table 4.1 offers an overview of all the modules and their inputs and 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 scale of flexibility management system in the power market and thus estimate the value of flexibility management market. Furthermore,

Table 4.1: List of modules

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

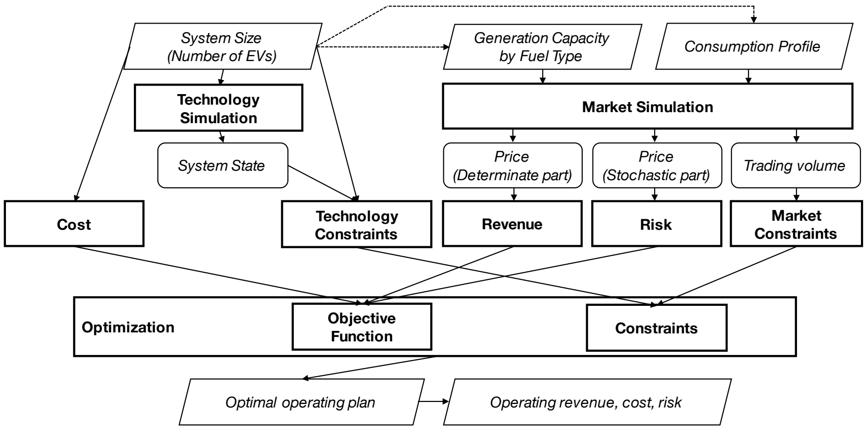

Figure 4.1: Flow chart of the techno-economic model

we can assess the impact of driving factors including renewable penetration, cost reduction, and the possible diminishing return with increasing flexibility.

4.2 Market-based modules

4.2.1 Revenue module

In this study, we only consider explicit revenues from power markets. At each time step (t), the revenue (REV_t) is calculate as the amount of energy (e_t, in MWh) offered in each energy market segment (i), and/or amount of reserve (r_t, in MW) offered in each reserve market segment (j), multiplied by their corresponding prices (π_t, in \$/MWh or \$/MW). In reserve market, there are additional revenues from energy provision while the committed capacities are activated. The amount of energy delivered in reserve market is determined as a proportion of the committed reserve using a term of ratio (δ_t, in MWh/MW). The total revenue within a given period of time (T) and a set of selected energy markets (I) and a set of selected reserve markets (J), can be then computed as:

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

where, d and c in the superscripts denote ”discharge” (to release energy from flexibility resources to grids) and ”charge” (to intake energy from girds to flexibility resources) respectively. $e_t^{d,i}$, $e_t^{c,i}$, r_t^j, are endogenous variables 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 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 flexibility resource can be reallocated to make offers to different market segments, i.e. performing multitasking. These cases need to be carefully managed to comply with actual market rules. Detailed treatments regarding multitasking are illustrated in section 4.5.

The ratios δ_t are computed based on the real control signal when data is available, 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 historical data or from the outputs of market simulation module described in Section 4.2.3.

We re-formulate Equation (4.1) in form as:

$$\mathrm{REV} = \boldsymbol{f}\, X$$

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

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

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

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

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

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

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

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

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

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

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

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]:

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

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 uncorrelated 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 formulated in vector and matrix 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 flexibility with a dynamic market condition is still a challenging task. While investment decisions 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 coarse resolution is sufficient, and visual arbitrageurs who have almost no investments on infrastructures and may perform decision-makings with a short-term perspective. A holistic approach combining these researches were taken sometimes [24][25] but may easily bring in unnecessary 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 simplifying 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 sub-model 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 matured 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 Chapter 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 flexibility provision in current energy markets so that we can simulate the market conditions when the flexibility 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 contrast, 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 curve 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 investigation into the flexibility of power plants is necessary.

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

- Overall bandwidth of operation: the range of output between minimum and maximum load;

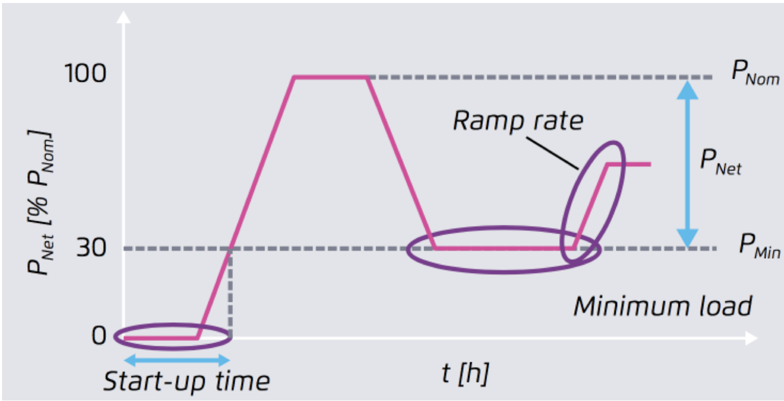

Figure 4.2: Qualitative representation of key flexibility parameters of a power plant[29]

- 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 typically 30 minutes[30][31] so can be considered as flexible generation.

For a steam-turbine power plant, the minimum operational load is about 25-60% of its nominal capacity 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 procedure for a certain generation source is decribed as following and shown as Figure 4.2.3:

1. Make the duration curve of the generation data, and obtain $\overline{c}^{mid.}$ which is the range that the generation source is operating for over 10-99% of

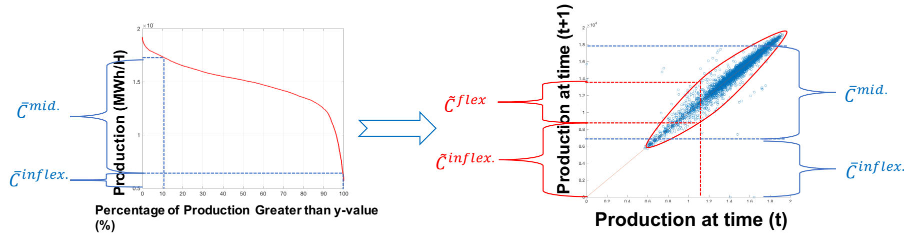

Figure 4.3: Schematic illustration of determining bounded flexibility for limited flexible generations

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 envelop lines which limit the production at time $t+1$ based on production at time t. With a certain production p_t, p_{t+1} 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. Finally, we find the relationship that map the production at time t to flexible capacity at time $t+1$ as:

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

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

$$\begin{aligned} c_{t+1}^{peak} &= \mathcal{C}^{peak}(P_t) \\ &= max\{\tilde{c}_t^{flex.} + \tilde{c}_t^{inflex.} - (\bar{c}^{mid.} + \bar{c}_t^{flex}), 0\} \end{aligned} \tag{4.22}$$

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 uncertainty 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:

$$\pi_t^{RT} = \kappa(\pi_t^{DA} + \alpha) + \epsilon_t \tag{4.23}$$

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 flexibility 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

$$\begin{bmatrix}\Gamma^d & | & \Gamma^c & | & \Gamma^r\end{bmatrix} X \leq \boldsymbol{b} \tag{4.24}$$

Most of the market constraints 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:

$$C^{ini} = C^s\overline{s} + C^r\overline{r} + C^0 \tag{4.25}$$

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):

$$C^{EAC} = \frac{C^{ini}}{\frac{1-\frac{1}{(1+r)^a}}{r}} \tag{4.26}$$

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):

$$C^{fix} = C^{EAC} + C^{fO\&M} \tag{4.27}$$

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 summarized as following:

- Modelling battery degradation itself is a complex engineering problem as it is affected by a list of physical parameters, including the degree-of-discharge (DoD), state-of-charge (SoC), charging/discharging rate, temperature, etc.[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]

Degradation 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 operational 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 throughput per day[33]. Nonetheless, it was also pointed out by [33] that while assuming degradation cost being zero, the operational planner would tend to operate the system more frequently, which would possibly in turn to violate the assumption of zero-degradation.

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 throughput* $|e^t|$ 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 technique used in researches for estimating battery degradation[39][41].

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

$$C_t^{degradation} = \zeta(\sum_i^{i\in I}(e_t^{d,i} + e_t^{c,i}) + \sum_j^{j\in J}(\delta_t^{j,+} + \delta_t^{j,-})r_t^j) \tag{4.28}$$

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

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

$$\delta_t^{j,-} = \begin{cases} 0 & \delta_t^j \geq 0 \\ -\delta_t^j & \delta_t^j < 0 \end{cases} \tag{4.30}$$

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 (4.28) 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 (4.29) and (4.30).

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

$$\Delta^- = diag(\delta_1^{J(1),-}, \dots, \delta_T^{J(1),-}, \dots, \delta_1^{J(|J|),-}, \dots, \delta_T^{J(|J|),-}) \tag{4.32}$$

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 neglectable 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 capacity. The state is determined using Equation 4.33.

$$s_t = \eta_s s_{t-1} + \eta_c(\sum_i^{i\in I} e_t^{c,i} + \sum_j^{j\in J} \delta_t^{j,-} r_t^j) - \frac{1}{\eta_d}(\sum_i^{i\in I} e_t^{d,i} + \sum_j^{j\in J} \delta_t^{j,+} r_t^j) \tag{4.33}$$

In order to formulate Equation (4.33) 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 (4.33).

$$S = \eta_s H S_0 + \left[-\frac{1}{\eta_d} H^I \quad | \quad \eta_c H^I \quad | \quad H^J(-\frac{1}{\eta_d}\Delta^+ + \eta_c \Delta^-) \right] X \tag{4.34}$$

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 (4.34) as:

$$S = \boldsymbol{h}_0 + \boldsymbol{h}\, X \tag{4.35}$$

where

$$\boldsymbol{h}_0 = \eta_s H S_0 \tag{4.36}$$

$$\boldsymbol{h} = \left[-\frac{1}{\eta_d} H^I \quad | \quad \eta_c H^I \quad | \quad H^J(-\frac{1}{\eta_d}\Delta^+ + \eta_c \Delta^-) \right] \tag{4.37}$$

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 storage:

- 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 and analyzed separately

It shall be noticed with the dynamic storage model, only the overall state on the whole system level, i.e. the aggregation of all EVs in the system, is monitored and complied with the technological constraints. Performing simulation and optimization for each EV with a distributed approach is beyond the scope of this study.

In order to transform the model for ESS to be dynamic in size and availability, 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.

$$n_t = n_{t-1} + n_t^+ - n_t^- \tag{4.38}$$

The energy stored in each EV while being plugged-in or plugged-out are denoted as s_t^+ and s_t^-, respectively. n_t^+, n_t^-, s_t^+ and s_t^- can be determined statistically from real vehicle driving profiles.

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

$$\begin{aligned} s_t =& \eta_s s_{t-1} + \eta_c(\sum_i^{i\in I} e_t^{c,i} + \sum_j^{j\in J} \delta_t^{j,-} r_t^j) - \frac{1}{\eta_d}(\sum_i^{i\in I} e_t^{d,i} + \sum_j^{j\in J} \delta_t^{j,+} r_t^j) \\ &+ s_t^+ n_t^+ - s_t^- n_t^- \end{aligned} \tag{4.39}$$

The matrix form of Equation (4.38) is as following:

$$N = I_{T\times T} N_0 + L_{T\times T} N^+ - L_{T\times T} N^- \tag{4.40}$$

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

$$N = \begin{bmatrix} n_1 & n_2 & \dots & n_T \end{bmatrix}^T$$
$$N_0 = \begin{bmatrix} n_0 & n_0 & \dots & n_0 \end{bmatrix}^T$$
$$N^+ = \begin{bmatrix} n_1^+ & n_2^+ & \dots & n_T^+ \end{bmatrix}^T$$
$$N^- = \begin{bmatrix} n_1^- & n_2^- & \dots & n_T^- \end{bmatrix}^T$$
$$S^+ = diag(s_1^+, s_2^+, \dots, s_T^+)$$
$$S^- = diag(s_1^-, s_2^-, \dots, s_T^-)$$

Analogously, translating Equation (4.39) to matrix form leads to:

$$\begin{aligned} S = {} & \eta_s H S_0 + H S^+ N^+ - H S^- N^- \\ & + \left[-\tfrac{1}{\eta_d} H^I \;\mid\; \eta_c H^I \;\mid\; H^J(-\tfrac{1}{\eta_d}\Delta^+ + \eta_c \Delta^-) \right] X \end{aligned} \tag{4.41}$$

which can be reformulated as:

$$S = \boldsymbol{h}_0 + \boldsymbol{h}\, X \tag{4.42}$$

where

$$\boldsymbol{h}_0 = \eta_s H S_0 + s^+ H N^+ - s^- H N^- \tag{4.43}$$

$$\boldsymbol{h} = \left[-\tfrac{1}{\eta_d} H^I \;\mid\; \eta_c H^I \;\mid\; H^J(-\tfrac{1}{\eta_d}\Delta^+ + \eta_c \Delta^-) \right] \tag{4.44}$$

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 charging/ discharging rate shall be bounded at its maximum rate ($\overline{r}$, assuming symmetric for charge and discharging).

$$0 \leq \frac{1}{\Delta t} \sum_i^{i \in I} e_t^{d,i} + \sum_j^{j \in J} r_t^j \leq \overline{r} \quad \forall t \in T \tag{4.45}$$

$$0 \leq \frac{1}{\Delta t} \sum_i^{i \in I} e_t^{c,i} + \sum_j^{j \in J} r_t^j \leq \overline{r} \quad \forall t \in T \tag{4.46}$$

It can be noticed that opposite movement of charging/ discharging in different markets are not offset in the constraints. This implies virtual arbitrageurs are not allowed to make deals that cannot be afforded physically although the physical systems are not actually activated.

Meanwhile, the energy stored is restricted as well.

$$0 \leq s_t \leq \overline{s} \quad \forall t \in T \tag{4.47}$$

Replacing s_t using Equation (4.33), the contraint is formulated as:

$$0 \leq \eta_s s_{t-1} + \eta_c (\sum_i^{i \in I} e_t^{c,i} + \sum_j^{j \in J} \delta_t^{j,-} r_t^j) - \frac{1}{\eta_d} (\sum_i^{i \in I} e_t^{d,i} + \sum_j^{j \in J} \delta_t^{j,+} r_t^j) \leq \overline{s} \tag{4.48}$$

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

$$-\frac{1}{\Delta t}\left[\overbrace{I_{T\times T}|\dots|I_{T\times T}}^{|\mathrm{I}|}\,|\,\overbrace{O_{T\times T}|\dots|O_{T\times T}}^{|\mathrm{I}|}\,|\,\overbrace{I_{T\times T}|\dots|I_{T\times T}}^{|\mathrm{J}|}\,|\right]X \leq 0 \quad (4.49)$$

$$-\frac{1}{\Delta t}\left[\overbrace{O_{T\times T}|\dots|O_{T\times T}}^{|\mathrm{I}|}\,|\,\overbrace{I_{T\times T}|\dots|I_{T\times T}}^{|\mathrm{I}|}\,|\,\overbrace{I_{T\times T}|\dots|I_{T\times T}}^{|\mathrm{J}|}\,|\right]X \leq 0 \quad (4.50)$$

$$\frac{1}{\Delta t}\left[\overbrace{I_{T\times T}|\dots|I_{T\times T}}^{|\mathrm{I}|}\,|\,\overbrace{O_{T\times T}|\dots|O_{T\times T}}^{|\mathrm{I}|}\,|\,\overbrace{I_{T\times T}|\dots|I_{T\times T}}^{|\mathrm{J}|}\,|\right]X \leq \overline{R} \quad (4.51)$$

$$\frac{1}{\Delta t}\left[\overbrace{O_{T\times T}|\dots|O_{T\times T}}^{|\mathrm{I}|}\,|\,\overbrace{I_{T\times T}|\dots|I_{T\times T}}^{|\mathrm{I}|}\,|\,\overbrace{I_{T\times T}|\dots|I_{T\times T}}^{|\mathrm{J}|}\,|\right]X \leq \overline{R} \quad (4.52)$$

where $O_{T\times T}$ is a $T \times T$ zero matrix and

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

The constraints of storage are formulated as:

$$-\boldsymbol{h}\, X \leq \boldsymbol{h}_0 \quad (4.53)$$

$$\boldsymbol{h}\, X \leq \overline{S} - \boldsymbol{h}_0 \quad (4.54)$$

where, $\boldsymbol{h}$ and $\boldsymbol{h}_0$ are determined by Equation (4.35) to (4.37), and

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

Electric vehicle to grid

The constraints for ESS are generally portable for the EV2G systems, by simplying re-using Equation (4.42) to (4.44) to derive $\boldsymbol{h}$ and $\boldsymbol{h}_0$, and replacing the upper bound limit in Equation 4.51 with

$$\overline{R} = \overline{r}N \quad (4.55)$$

where, N is determined by Equation (4.40).

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 reasonable operation patterns that simulate the behaviors of those players. For this sake, we employ an 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:

$$\underset{X}{max} \left[(1-\beta)\left(Revenue(X) - C^{degradation}(X)\right) - \beta CVaR(X)\right] \tag{4.56}$$

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 special 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 predictable 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:

$$\hat{\pi}_t = \hat{\pi}_{t-t_w} \cdot \frac{\sum_{t-t_w+1}^{t-t_d} \pi_\tau}{\sum_{t-t_w-t_w+1}^{t-t_w-t_d} \pi_\tau} \tag{4.57}$$

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 easily 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 and restricted by the rate constraints in Section 4.3.3. 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-generating 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-generating resource to provide service 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.

Although some system operators have already implemented special energy neutral signals for the emerging flexibility resources, it is not a universal practice 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 purchasing 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

PJM: symmetric (self-schedule, pool-auction), obligation (load contributing factor), market-based, imbalance(enforcement, 10% waved for VRE),

Germany: asymmetric (balancing energy market vs frequency control market),

AEMO: asymmetric (AEMO pays for provider, charge regulation from either all generators or all consumers, and charge contingency from causer)

The super-set 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 Quantitative studies and results

So far we have discussed qualitatively the existing and potential opportunities for flexibility managment in the three geographies, and screened the possible business cases. Further to that, it is necessary to perform quantitative analysis in order to understand:

- **Market Size:** the potential value creation in the market for flexibility management solutions, subject to certain generic system dynamics but without respect to cost dyanamics of specific technologies
- **Profitability:** the metric to judge whether a specific technology is profitable or not to extract certain amount of value from current or future markets taking into account cost elements

Based on the methodology introduced in Chapter 4, we performed experiments with consideration of constaints from both markets and technologies. All three markets discuess previously and two technologies, i.e. energy storage system (ESS) and Electric vehicle to grid (EV2G), were studied.

Specifically, the ESS with a system dyanmic that is able to release and absorb energy can be deemed as a generic flexibility source. The revenue derived using ESSs can be viewed as a reference of the maximum market potential from flexibility managment. Meanwhile, with cost parameters of a typical battery energy storage system (BESS), we can analyze the profitability of BESSs with results involoving elements of costs.

On the other hand, EV2G is served as a more peculiar example of technology, with additional case-specific constaints like the EV driving behaviors compared to a generic ESS. Maximum revenue from this technology shall be bounded by values derived from the generic ESS, but the profits may deviate significantly from values of BESSs, as their cost dynamics and business models could be distinct with other. Details are to be introduced later in this section.

Two types of works were carried out. We first examined the value of markets for flexibility management under current market conditions, i.e. based on historical observations without involving the market simulation module (Section 4.2.3). This allows us to obtain some concrete numbers to establish a comprehensive understanding toward the value of flexibility management in nowadays' power markets.

Thereafter, as markets evlove rapidly especially with the disruption of fast-growing renewable generations, a view toward future market development is also necessary. As a immature business, valuation of markets for flexibility management would be sensitively affected by various factors. The multi-dimentional variances and unpredictable changes on non-technical issues like market design and regulatory adjustments make it almost impossible to accurately forecast the market size and profits in the future. Nonetheless, understanding the impacts of some key factors would provide us valuable guidances on the directional movement of the market and thus offer viable references for technology vendors' decision makers.

5.2.1 Data, paramters and valuation metrics

The electricity market data including price and volume in each marketplaces correspond to the actual market data from January 1st 2016 to December 31st 2016. While general rules for accounting and data availability have been discussed in Section 5.1, detailed pre-processes and how they were fitted in as inputs of our valuation model can be found in Appendix A.

For cost determinations, we would first use figures based on the present market pricing level, and then make scenarios with reduced costs to find the break-even point if it is not yet profitable. According to the International Renewable Energy Agency (IRENA)[50], the cost for battery energy storage systems was analyzed as proportional to their energy capacity, $\overline{s}$, and the energy cost coefficient, C^s, for state-of-the-art lithium-ion batteries were reported to be ca. $\$350/kWh$ in 2016. The replacement cost were based on actual price from Tesla[51], one of the leaders in battery and electric vehicle markets. The operating life is set to be 6000 FCEs, which corresponds to an optimistic estimation by Sandia National Laboratories[52]. Designed life time is assumed to be 10 years. Discount rate is made as 10% as is discussed in Section 4.3.1. The technology costs were made to be zero so that the derived profits will be the margins that can be possibly realized by technology vendors. All the parameters for cost calculation are summarized in Table 5.1.

Table 5.1: Parameters for cost calculation

Items	**Unit**	**Value**
Energy cost coefficient, C^s	$\$/kWh$	350
Power cost coefficient, C^r	$\$/kW$	0
Technology cos,t C^0	$\$$	0
Replacement cost coefficient, C^s	$\$/kWh$	150
Designed life time	*year*	10
Operating life time	*FCE*	6000
Discount rate	%	10

It is worthwhile to point out again that by using the parameters described above, the ESSs are virtually battery energy storage systems (BESSs). This fits the purpose of case studies. However, the conclusions on profitability are not portal for other types of ESS, but it does not mean the methodology loses its generality. The value of revenue would still be valid for other types of technology as long as they can have the same function of shuffling energy between time slots. Furthermore, by using different data as inputs, our model can be utilized for analysis of profitability of other energy storage systems with different cost dynamics.

In terms of EV2G studies, we first determined the battery parameters of EVs.

- EV charging rate is 10kW, corresponding to the guidance provided by Tesla[53] and a typical home charging infrastructure with 50A current limit.
- The battery energy capacity per EV of 75kWh is taken from one of the most popular EV models[54].

Simulations are then performed to get EV driving profiles, which are based upon data from the California Department of Transportation's California Household Travel Survey for 2010-2012[55]. This survey carried out multiple objectives and included 79011 vehicles. For our work we focus on a proportion of the vehicles, 2910, which were fitted with GPS. These vehicles were monitored continuously for a 7-day window with the 1-second resolution. The GPS data is then processed into trip profiles, while include information of the location of each EV at each time step as well as the trips made by each EV. Furthermore, together with the parameters of the EV model we have selected above we simulated the SoC time series of the EV batteries. Finally, from the simulated results, we can statistically derive the value of probability distribution of EV plug-in n^+, plug-out n^-, and average state-of-charge (SoC) of batteries plug-in s^+, plug-out s^-, as introduced in Section 4.3.2. The results are shown as Figure 5.1-5.2 where we can see clear periodic patterns that are different between weekdays and weekends.

The metrics to evaluate the system performance are slightly different between ESS and EV2G. For ESS, the criteria in the evaluation metrics include

- **Revenue:** the total explicit revenue from electricity markets calculated as Equation (4.1), per annum
- **Operating Profit**: the total revenue net of operation-dependent costs (degradation cost), per annum
- **Profit:** the total revenue net of both operation-dependent and fixed costs, per annum

For EV2G, the fixed cost that is mainly related to procuring the battery stocks shall not be considered for a technology vendor. Furthermore, the implicit charging cost to compensate the energy consumed by EV driving are listed separately. Depending on the specific business model in practice, a portion of the implicit charging cost may be recovered by the technology

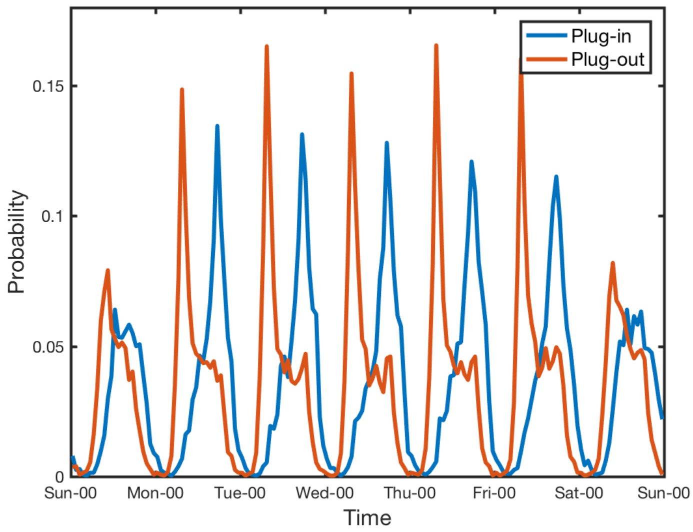

Figure 5.1: Probability of EV plug-in/ plug-out

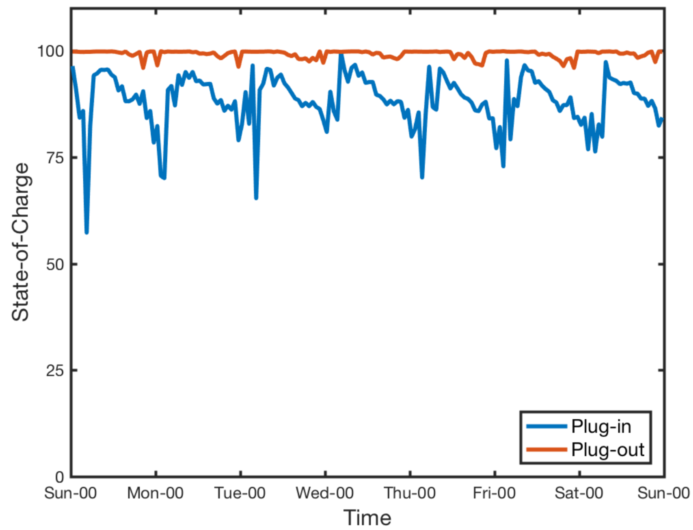

Figure 5.2: Average SoC of EV when plug-in/ plug-out

vendors from the end-users, although in this thesis we did not exclude it from calculating the profit. As a result, the criteria are altered as:

- **Revenue:** the total explicit revenue from electricity markets calculated as Equation (4.1), per annum
- **Implicit Charging Cost**: the cost of energy compensation for EV driving demands, calculated as the total energy consumption multi-

plied by average price over the span of one operational cycle, per annum

- **Profit:**: revenue net of costs including the implicit charging cost and battery degradation. The investments on technology are made to be zero as is discussed at the beginning of this section, per annum

As a result, the profit of a EV2G system is closed to the concept of operating profits for a ESS, which excludes the investment of procuring batteries. This implies two disparate business models. Cautions shall be raised while comparisons between these two technologies are made.

In order to determine the profitability and market size of ESS, we evaluated the system performance with different total sizes. Thereafter, we would select some key states in order to extract the most informative indicators to technology vendors. Overall, 4 scenarios would be analyzed and are illustrated by Figure 5.3 using an example with typical curve shapes. This example shows the results for a case of making arbitrage in day-ahead, real time energy markets and simultaneous delivering regulation services in PJM electricity markets.

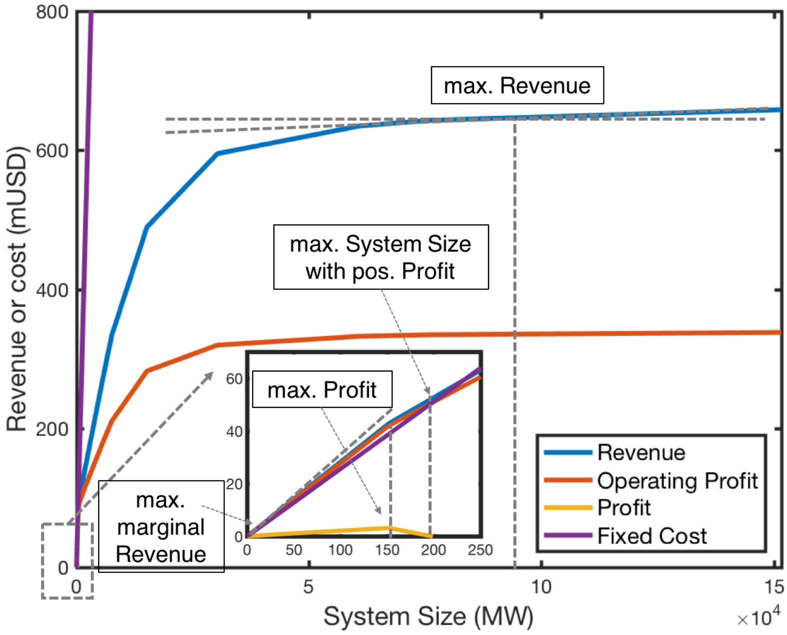

Figure 5.3: Graphic illustration of 4 scenarios

Two the most crucial states are:

- "**max. Revenue**": the state where the maximum potential revenue is extracted from the markets. The "max. Revenue" state is determined as when the marginal increment of revenue is less than 5% with additional system capacity, i.e.

$$\frac{\Delta \text{Revenue}}{\Delta \text{System Size}} < 0.05$$

Since in our studies, we found the operating profits are always in line with revenue, so this state is equivalent to"**max. Operating Profit**".

The value of revenue in this scenario can present a reference of maximum market potential, i.e. maximum amount of revenue can be possibly realized, without respect to the costs. Profits tend to be negative in this scenario with inflated system size. However, it could still provide informative indicators to technology vendors as they might be able to develop technologies with lower costs than what we calculated in the case studies.

- "**max. marginal Revenue**": the state where the marginal incremental revenue is maximized.

  Since in our study, we found the operating costs were always in line with the revenue while the fixed cost were proportional to the system size. As a consequence, this state is always achieved with the smallest ESS size simulated when the market constraints are rarely activated.

  This state indicates the maximum potential return per unit system so reveals the profitability at the most optimistic condition. In order to make results be understood more intuitively, we would normalize the values in this scenario to be per unit system size.

In addition, if the profit was found to be positive in the scenario of "max. marginal Revenue", there are two more states that are worthwhile to draw attention to:

- "**max. System Size with pos. Profit**": the state indicating maximum possible system size where the profit is barely above zero. Since in our studies the profit either drops monotonically or decreases after an initial rise, this state is obtained when the profit falls to be 0.

  This scenario would inform technology vendors about when the market would be saturated. Without revolutionary innovations on technologies or drastic changes on market conditions, expanding the flexibility fleet beyond this scenario is likely to create losses rather profits.

- "**max. Profit**": the state where the profit is maximized.

  If the total system size goes beyond this scenario, it indicates that the competition will intensify and the profit will drop with additional market entrants.

These two scenarios would not exist if the profit in the scenario of "max. marginal Revenue" is negative as it means the marginal revenue and marginal operating profits would never exceed the marginal fixed cost that is constant.

Overall, "max. marginal Revenue" indicates the potential market size, and the rest three scenarios illustrates the profitability and profitable market size with the pre-defined cost paramters.

In terms of EV2G, the size of the system (number of EVs) are not strongly related to the profitability of EV2G, if at all. Therefore, it makes no sense to analyze the optimal system size in relation to the profitability. Instead, we would show the market values under certain scenarios where the number of EVs is determined externally.

Table 5.2: The metrics of scaling the market by average comsumption rate and metering points

Geography	**Consumption (MW)**	**MP**
Germany	59 138	51 869 730
PJM	87 793	30 331 401
NSW	7978	3 364 428

Finally, we would normalize results with respect to the overall scale of the market, in order to make cross-regional comparison more intuitive. The main metric to represent the scale is the average consumption rate (in MW) in the whole market. Consequently, values of cash flows would be shown in unit of million USD per year per MW consumed (USD/(a $\cdot$ MW)). Meanwhile, the metering point (MP) is taken as a auxiliary metric and would be mentioned in certain circumstances as it represents the number of end-consumers in a market. The average consumption rates were obtained from the power markets data in 2016 and the statistics of MP are provided by commercial market data provider, Northeast Group[56][57][58]. All the relevant numbers are listed in Table 5.2.

The currency exchange rates are determined as the real market data as of January 1st 2018, when 1 EUR is equal to 1.20 USD and 1 AUD is equal to 0.78 USD[59].

5.2.2 Value of markets under current market conditions

This section presents the results using historical market data. Since two types of technologies and markets in three geographies were studied, there are a total of six distinct setups with each comprises serveral use-cases. In addition, we included a cost break-even analysis specifically for ESSs as few profitable opportunities were found due to high costs on battery stocks.

ESS in Germany: opportunities hidden by adverse market design of balancing energy and frequency control

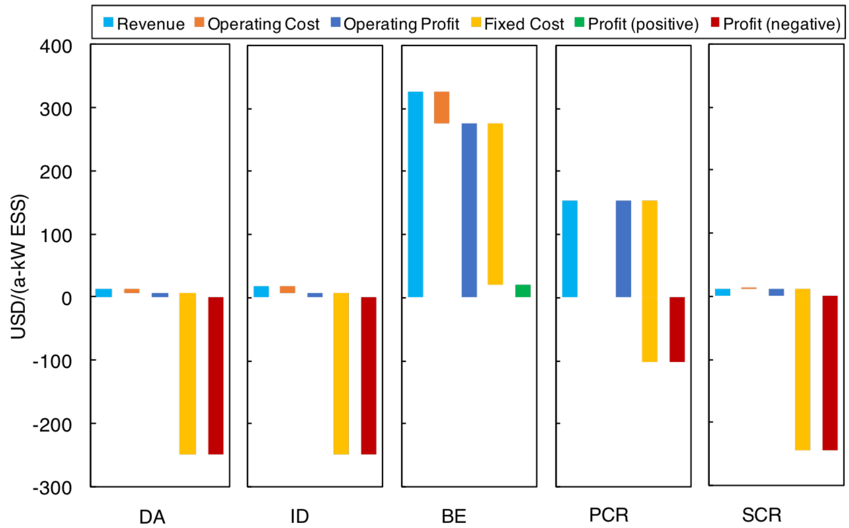

Figure 5.4: Profitability of ESS in Germany electricity markets in the scenario of "max. marginal Revenue"

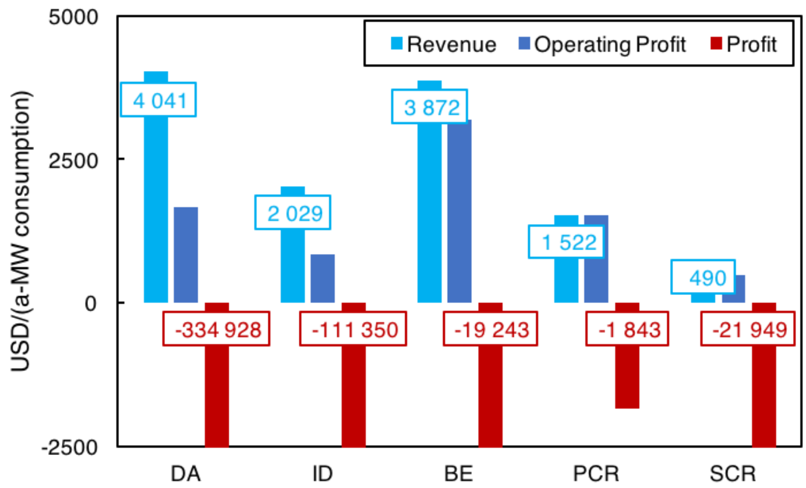

Figure 5.5: Market size of ESS in Germany electricity markets in the scenario of "max. Revenue"

As is discussed, profitability analysis can be performed using the scenario "max. marginal Revenue", the results of which are depicted by Figure 5.4. By showing values per unit ESS system installed, we can see the maximum unit return of ESS in Germany power markets.

Meanwhile, with ample size of ESS, maximum potential market sizes can be derived, corresponding to the scenario "max. Revenue". Summarized by Figure 5.5, annual cash flows are shown per MW consumption as normilzed values to the overal average consumption, 59 138 MW . For example, the normalized revenue for arbitrage in day-ahead market is 4041 USD per year per MW consumption, which indicates the achievable revenue for a power system in Germay with 1 MW average load and corresponds to 239 mUSD/a in whole German market by mutiplying the base of 59 138 MW.

It was found that the only profitable case is delivering balancing energy. As is analyzed in Section 5.1, this case corresponds to the situation of self-balancing where the players turn to the flexibility resource in avoidance of charges by TSOs for their imbalances. We further analyzed the maximum profitable system size and maximum profit of using the pre-defined BESSs; see Figure 5.6.

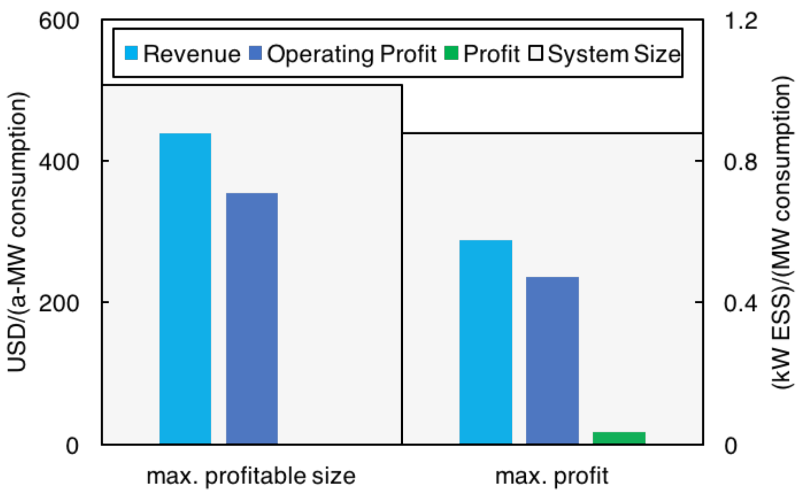

Figure 5.6: Market size of ESS in Germany electricity markets in the scenario of "max. System size with pos. Profit" and "max. Profit"

It can be seen from Figure 5.6, if being operated optimally BESSs with a size of up to 1 kW/(MW consumption) can generate profits by serving balancing energy, corresponding to a total 60MW in Germany. Nevertheless, it is challenging to be realized in practice. Market players do not have the right information to optimize their operational plans, since the balancing energy price, reBAP, is calculated *ex-post* and highly volatile, hardly predictable, as is discussed in Section 5.1. On the contrary, if a system is designed to have ample size and tackle almost all imbalance events, it corresponds to a situation as the "max. Revenue" scenario where we see negative profits from Figure 5.4.

On the other hand, we noticed from Figure 5.4 that selling frequency control services to TSOs is less economically viable than using BESSs for self-balancing.The maximum marginal revenue from self-balance is significantly higher (33 times) than from selling frequency control products, while ideally the situation shall be reversed. The balancing energy charges are designed to recover the costs of activating frequency control services (calling for energy delivery) while the costs paid for securing capacity commitment are socialized, as have been fully discussed in Section 5.1. Theoretically, players shall get higher turnover in the frequency control markets than avoided balancing energy charges. Furthermore, the actual total payment for SCR in Germany is 176 mUSD in 2016 which is equavilent to 2976 USD/$(\mathrm{a} \cdot \mathrm{MW})$, while the maximum achievable revenue with BESSs are bounded at 490 USD/$(\mathrm{a} \cdot \mathrm{MW})$ as shown in Figure 5.5 with the rest 83.5% of the market is intangible for BESSs . Our results imply that the current design of frequency control markets is neither economically efficient nor technically feasible to integrate the emerging BESS resources, which verifies our analysis in Section 5.1. We have argued that hurdles exist against emerging BESS to participate in frequency control markets with the non-energy-neutral signals and block-wise offering, especially for SCRs which demand significantly higher energy delivery than PCRs.

Facing either lack of information transparency in balancing energy charges or unfavorable market rules in frequency control markets, BESS players have no feasible options in the current market setup to make profits.

However, we may argue this situation shall not be long-lasting. We have already seen that certain amount of BESS will be a cheaper option to defer the expense on imbalance settlements compared to what are currently incurred. The market operators shall develop well-designed frameworks to encourage the participation of these resources that are beneficial to lower the overall system costs. In reality, there are indeed debates proposing possible solutions on this issue, e.g. letting TSOs who have the most abundance of information own and dispatch the storage resources[60], re-engineering the pricing mechanism of balancing energy[17] and implementing favorable frequency control products for storage[33], etc.

As an implication for technology vendors, these possible movements on market designs shall be taken care of as it could suddenly turn over the feasibly profitability of using BESSs for balancing services.

Regarding arbitrages value in energy market, although the potential revenues are 4041 USD/$(\mathrm{a} \cdot \mathrm{MW})$ in day-ahead and 2029 USD/$(\mathrm{a} \cdot \mathrm{MW})$ in intra-day market, the losses would be incredibly high in order to materialize the revenue using BESSs; see Figure 5.5. Even in the scenario of maximum unit return, the losses are about 10-20 times of the revenue; see Figure 5.4. It is clear that the heavy investments on batteries cannot be recovered from making arbitrage in energy market. However, since the operating profits are always positive, if technology vendors can enable similar functions as BESS using technologies with smaller capital costs such as certain types of DR, it is still possible to make profits out of the market worth a total of over 300 mUSD per annum in Germany.

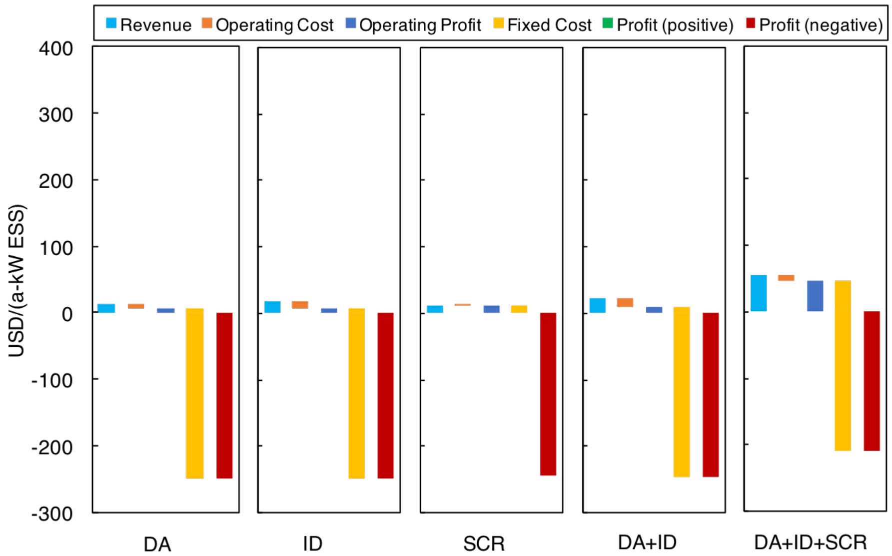

Figure 5.7: Profitability of ESS with multitasking in Germany electricity markets

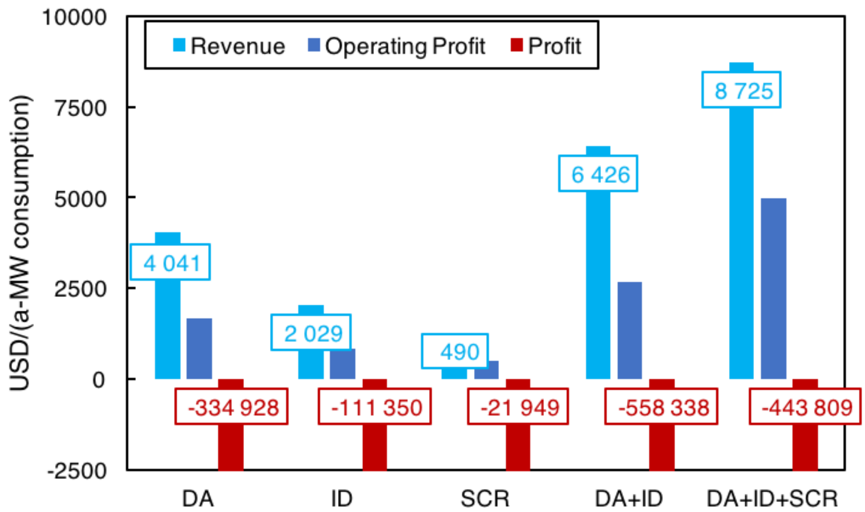

Figure 5.8: Market size of ESS with multitasking in Germany electricity markets

As has been discussed qualitatively, in order to increase the profitability and find a way to neutralize the frequency control signals, we may stack operations in day-ahead, intra-day and secondary control reserve for multitasking. Figure 5.8 shows the effects of multitasking.

While there are no significant synergies observed between day-ahead and intra-day markets (the unit returns remain unchanged in the scenario of maximum marginal revenue), stacking secondary control reserve with these two energy marketplaces will significantly improve the unit revenue (from 11 and 22 USD/(a · MW) to 54 USD/(a · MW)) as well as the maximum revenue potential (from 6426 USD/(a · MW) plus 490 USD/(a · MW) to 8725 USD/(a · MW)). The maximum unit operating profit, as a consequence, raises by 4.5 times. The increment of maximum potential revenue of 2299 USD/(a · MW) by stacking SCR on DA+ID indicates an additional revenue of 1809 USD/(a · MW) are accessible for ESS in the SCR markets, reducing the intangible part from 83.5% to 22.7%. This corresponds to our previous analysis that the non-energy-neutral signal is indeed an issue for BESSs and has to be neutralized externally. Nonetheless, coping with third-party energy transactions requires the BESSs spare certain capacity to receive or release the energy, which reduces their availability in delivering SCR services. This is reflected on the result that this case with multitasking is still not profitable.

To sum up, while arbitrage is mainly constrained by costs on the technology side, making profits from balancing services is limited by adverse market frameworks although it has already shown its ability to make a positive contribution to the system. Technology vendors shall consider other technologies than BESSs or expect drastic cost reduction of BESSs to unlock the arbitrage value worth over a total of 300 mUSD/a in Germany. Profits from balancing market are more technically tangible, yet adjustments on market frameworks are required.

ESS in PJM: successful practice of frequency control product design for flexibility

The results of case studies in PJM power markets are illustrated in Figure 5.9 and Figure 5.10.

As we can clearly see, the RegD marketplace that is specially designed for emerging flexible technologies is indeed profitable. This shall give merit to PJM's RegD design including the conditional signal neutrality, operational flexibility, and higher price as a result of introducing mileage ratio and beneficial factor, as have sufficiently discussed in Section 5.1; also refer to Appendix A. The market with a total size of 513 USD/(a · MW) can be wholly materialized by 2 kW/(MW consumption) BESSs without writing a loss, although the margin is very niche, barely above zero; see Figure 5.11.

Those merits allow BESS players to offer RegD alone without coupled operations in the energy market which is currently necessary in Germany's power markets. As a result, stacking it with the energy market does not improve the profitability and tangible market size as significantly as in Ger-

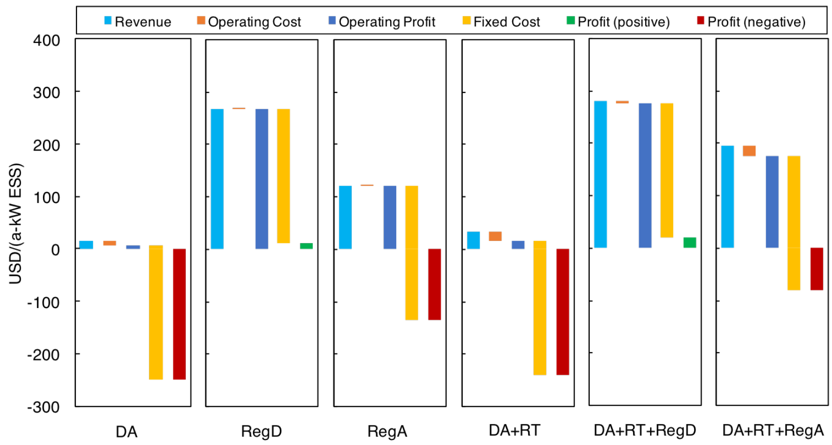

Figure 5.9: Profitability of ESS in PJM electricity markets in the scenario of “max. marginal Revenue”

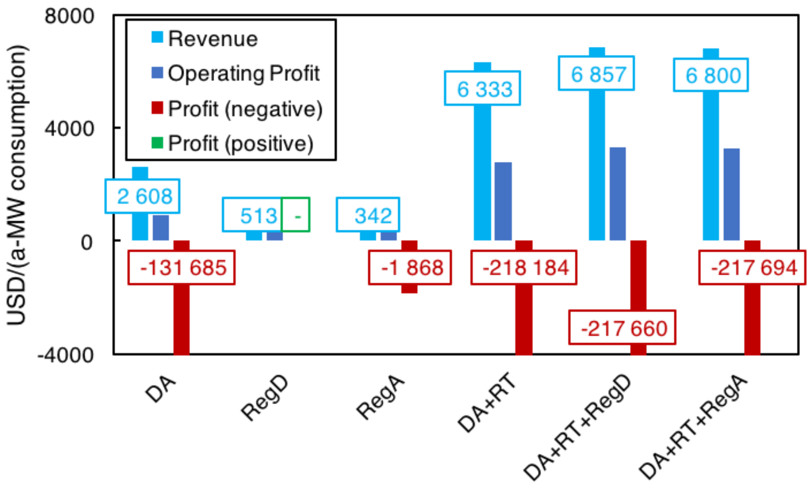

Figure 5.10: Market size of ESS in PJM electricity markets in the scenario of “max. Revenue”

many. As we can see from an example shown by Figure 5.12, the system with pre-defined parameters in this study will have slightly surplus energy while strictly following the RegD signal. The SoC would raise quite slowly so that the resource can sustain the provision of RegD service over a long period (at least 84 hours shown in the chart) without involving transactions in energy markets. Trading in energy market is activated to leverage the arbitrage potential due to extreme price movements, which is however infrequent. Serving RegD is preferred for most of the time due its higher profitability.

Apart from RegD market, there are no other profiting opportunities

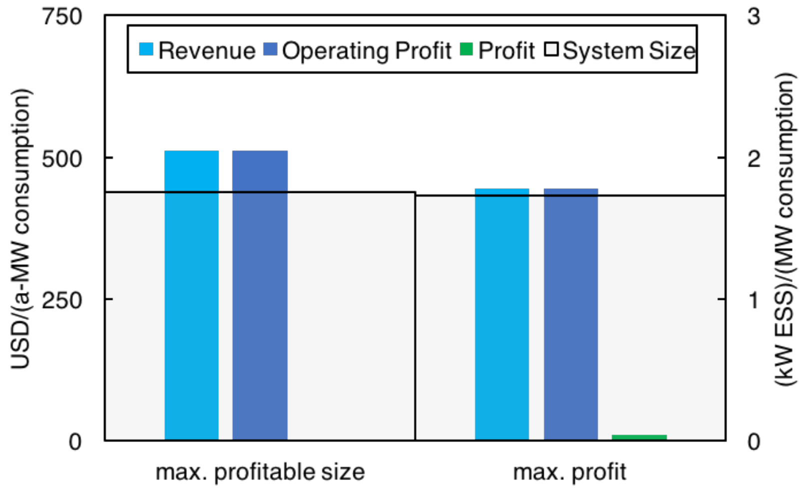

Figure 5.11: Market size of ESS in PJM electricity markets in the scenario of "max. System size with pos. Profit" and "max. Profit"

existing in PJM. Even the conventional regulation service RegA will create losses to BESS players.

Arbitrage in the energy market with flexibility through the so-called economic DR program, as is discussed in Section 5.1, is deemed not an ideal choice, especially in recent years when the electricity prices had fallen drastically with the shell gas revolution. As is discussed in Section 5.1, participating in the emergency DR program is a better option. However, the involvement of capacity market is not within our scope of quantifying the value, but the profiting mechanism is straightforward as is fully explained in the qualitative analysis.

Overall, PJM shows a perfect example on how to offer incentives for the emerging storage technologies that are beneficial to the system, by implementing proper market frameworks such as the RegD and the emergency DR program. For technology vendors, this market is already quite mature without spare space for new entrants unless significant changes may occur on market conditions, e.g. vast renewable penetration. Nonetheless, existing business cases in PJM may offer viable references for technology vendors to conduct similar practices in other markets.

ESS in NSW: most favorable market for arbitrage using flexibity yet still not profitable

In New South Wales power markets, we only studied the real-time energy market, which was primarily due to the limitation of data availability. Only information about total payment are available for the frequency control products. However, it was found that the overall size of these unaddressed

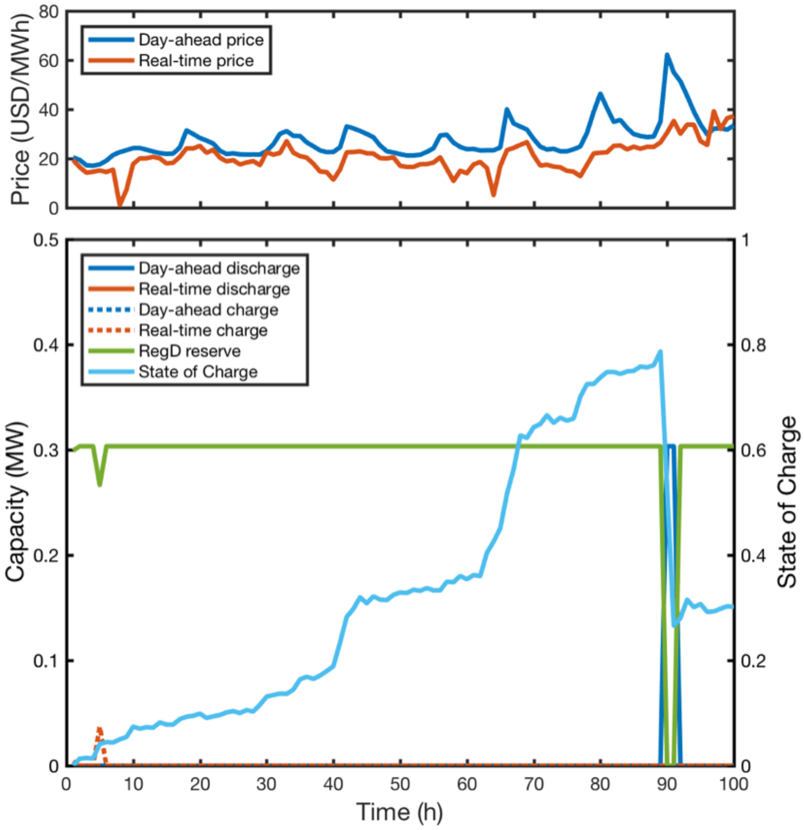

Figure 5.12: A example of operational plan with a 0.3MW battery energy storage system

markets are indeed negilible compared to the real-time energy market. The total payment for frequency control services in NSW was worth 23.4 mUSD (2933 USD/(a · MW)) in 2016, which was equal to just 0.53% of the total payment in the real-time energy market that was 4.4 bUSD (551 516 USD/(a · MW)). It was also much smaller than merely the arbitrage value, being 2.7% of the revenue from arbitrage of 109 301 USD/(a · MW) as shown by Figure 5.14. This reflects the philosophy of market design to fully exploit the ability of real-time energy market to response to the system imbalances which are otherwise tackled by frequency control markets[61][40]. As a result, the price volatility in NSW's real-time energy market is significantly higher than the energy markets in other geographies, as is shown by Table 5.3.

Such a volatile market is favorable for arbitrage. As we can see from Figure 5.13 and 5.14.Profitability-wise the marginal revenue per unit system, 83 USD/(a · kW ESS)) is 2.4 times the value of arbitrage in DA+RT in PJM and 3.8 times the value of arbitrage in DA+ID in Germany. In terms of

Table 5.3: The average and standard deviation of energy price in three geographies

Geography	Market	Average price (USD/MWh)	Standard deviation of price (USD/MWh)
NSW	RT	46.0	86.0
Germany	DA	34.8	15.0
	RT	35.1	16.1
PJM	DA	30.0	11.6
	RT	27.6	14.8

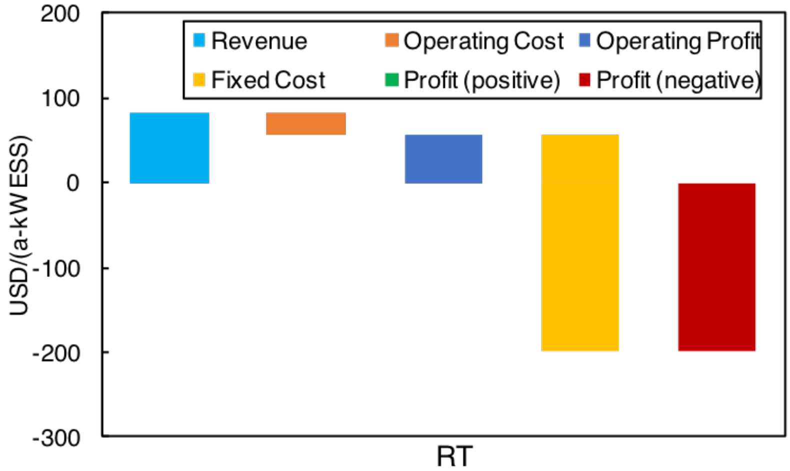

Figure 5.13: Profitability of ESS in NSW electricity markets in the scenario of “max. marginal Revenue”

market potential, the maximum arbitrage revenue 109 301 USD/(a · MW)) is roughly 17 times higher compared to either of those two arbitrage cases in Germany and PJM.

Nonetheless, even though in such a voltaile real-time energy market, it is still not a profitable business to deploy BESS in NSW for arbitrage.

Cost reduction: where is the break-even point for arbitrage using BESSs

According to the results above, using BESSs for balancing is already technically feasible while limitations lie on the aspect of market design. The value of arbitrage, however, is far away from being profitable due to high expenses on batteries. Overturn of arbitrage profitability using BESSs has to rely on reducing costs and changing market conditions. While the latter will be discussed in the proceeding section, hereby we present the results with reduced costs of battery stocks.

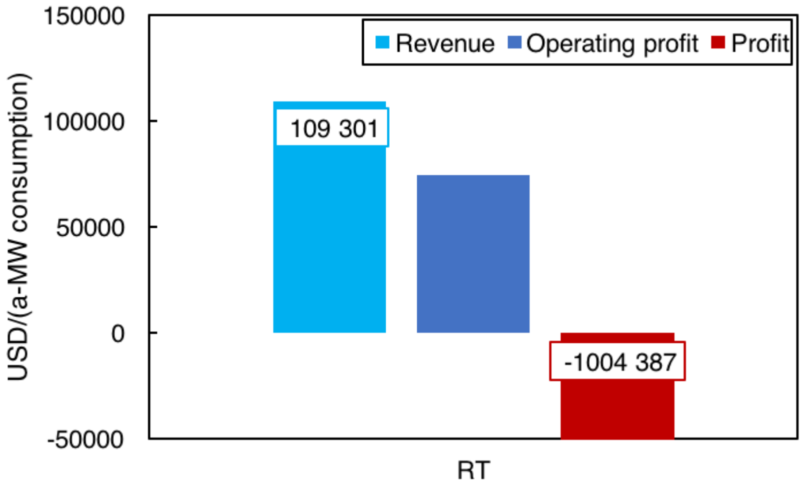

Figure 5.14: Market size of ESS in NSW electricity markets in the scenario of "max. Revenue"

In each geography, the case with the highest arbitrage potential was selected, which is respectively arbitrage in coupled day-ahead and intra-day market in Germany (DA+ID), arbitrage in coupled day-ahead and real-time market in PJM (DA+RT), arbitrage in real-time market in NSW (RT). The profitability is evaluated by the profitability ratio that is the ratio between the profit and overall costs including both operating and fix costs. We would show the maximum profitability ratio that is realized by a small size of BESS and meanwhile present the maximum profitable system size that is obtained as in the "max. System Size with pos. Profit" described previously.

Figure 5.15 - 5.17 illustrate how the profitability and market size will evolve with cost reduced by up to 95% in three geographies. The break-even point of costs is found to be 84%, 81% and 68%, respectively in Germany, PJM and NSW. If we adopt the forecast made by IRENA[50] who predict the cost reduction by up to 60% by 2030, none of these markets will be profitable for arbitrage by 2030. Even if we applied a constant learning rate of 14% per annum according to [34], the break-even point will be realized in 12, 11 and 8 years, respectively in Germany, PJM and NSW.

Moreover, it shall be noticed while the break-even point is just reached, the total profitable system size will be almost at zero. To materialize the whole potential of arbitrage revenue, it requires a cost reduction of 95%+, 95% and 90%, respectively in Germany, PJM and NSW, which is almost impossible to be realized in the foreseeable future.

As a conclusion, the cost reduction of BESS by learning effect alone will not turn over the profitability of arbitrage using BESSs in the near future. Unless revolutionary technical innovations happen, opportunities

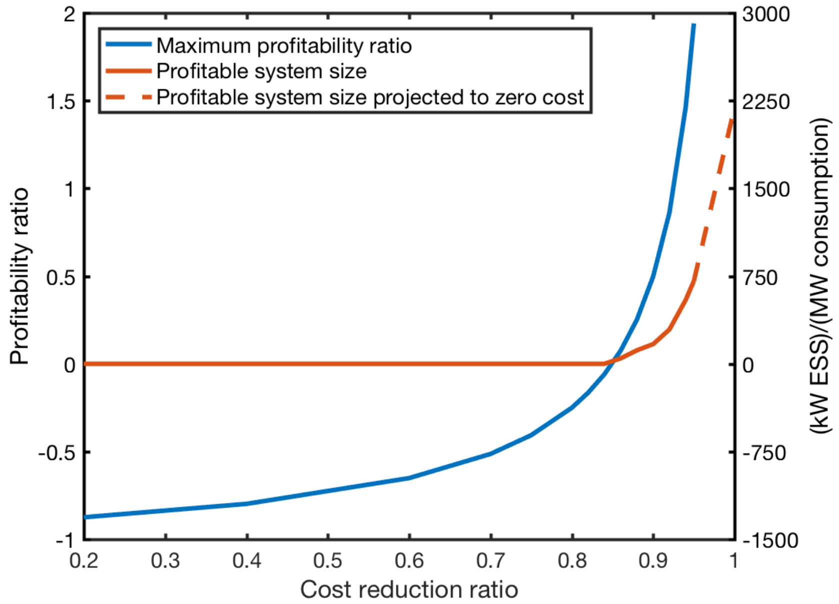

Figure 5.15: Development of market size and profitability of arbitrage in coupled day-ahead and intra-day markets with reduced costs in Germany

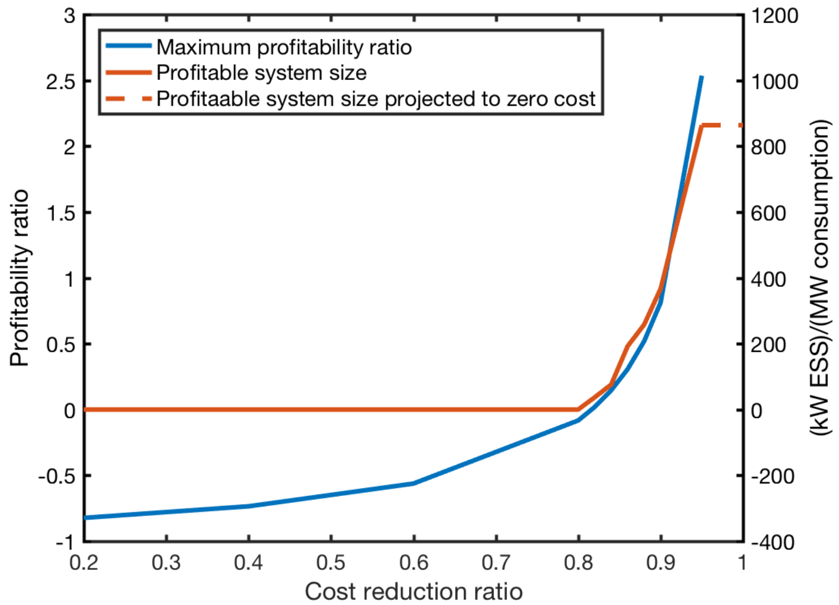

Figure 5.16: Development of market size and profitability of arbitrage in coupled day-ahead and real-time markets with reduced costs in PJM

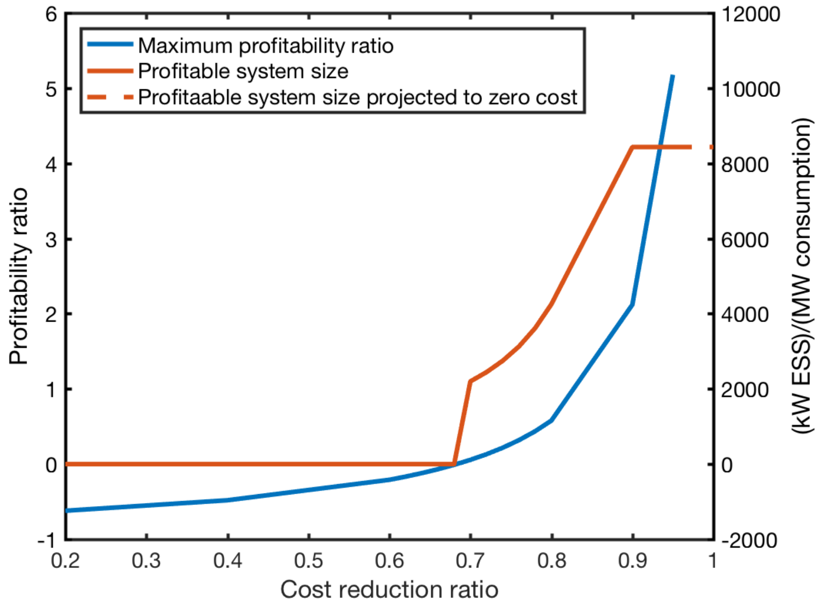

Figure 5.17: Development of market size and profitability of arbitrage in real-time markets with reduced costs in NSW

of arbitrage using BESS may only arise with drivers from the market, e.g. renewable penetrations, which are to be shown in Section 5.2.3.

EV2G in Germany: promissing and fast-growing opportunities

Implementing EV as a grid resource is not as straightforward as using generic ESSs that is discussed above. The main issue is that the energy demand for EV driving itself poses challenges to grid. It is not possible to deliver any services without incorporate a large-volume energy market. Therefore, the day-ahead energy market is always included for all the cases for EV2G. Moreover, in our case studies, it is found even with the day-ahead market, charging the EVs is not feasible while their number reached a certain level. In the optimization framework, the technology constraints would violate market constraints, especially the one that we set to restrict the activation of peak generation during non-peak hours, while the EV fleet grows beyond a certain scale. This corresponds to the situation where spare generation resources in the power system are not sufficient to fulfill the energy needs of EVs. The electricity price may raise significantly in those scenarios compared to nowadays's level. As is shown by Figure 5.18, when the number of EV is higher than 1 million, it start to stress the electricity supply if the generation capacity remains at present level.

This finding implies when there will be 1 million more EVs in Germany

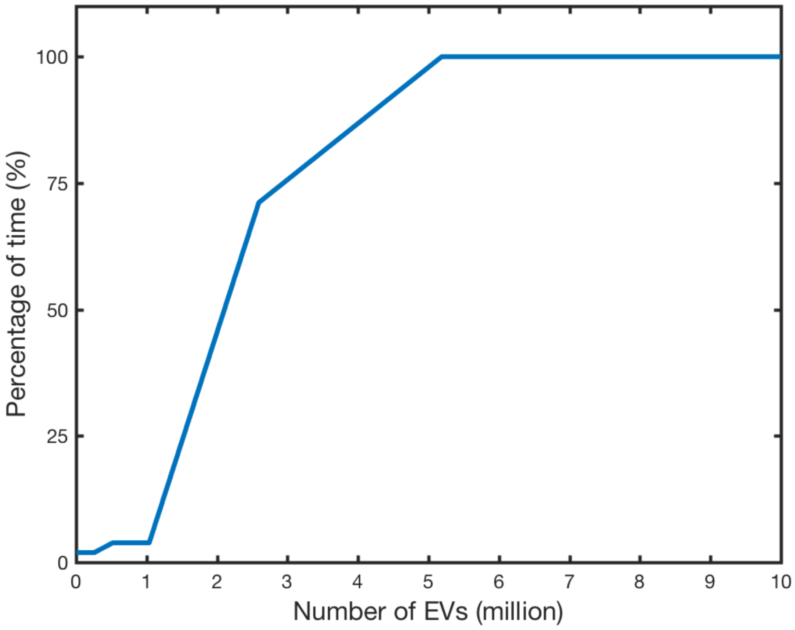

Figure 5.18: Percentage of time when EV charging demand cannot be fulfilled in Germany

compared to the number in 2016, it will create great incentives for infrastructure extension of electricity grid, which reveals a promising business opportunity. Nevertheless, studies under that condition is beyond the focus of our work. Instead, we would only perform scenario analysis when the number of EV is within the limit of 1 million.

In this thesis, we applied three scenarios studying the EV2G market in Germany:

- **EV number 2016:** assuming all EVs in Germany by 2016 are contract for delivering EV2G services
- **EV number 2017:** similar to the first scenario but using the data of 2017
- **2% market share:** assuming EVs will account for 2% of the total vehicle number in Germany (45 million according to [62]) i.e. 0.9 million EVs in the future

According to the Federal Motor Transport Authority of Germany (Kraftfahrt-Bundesamtes, KBA)[63], the number of plug-in electric vehicles has grown fast over the past year, especially in 2017. Since the EV registered before 2010 is negligible, we conceived the cumulative registration since 2010 as the total number of EVs in Germany, shown as Figure 5.19.

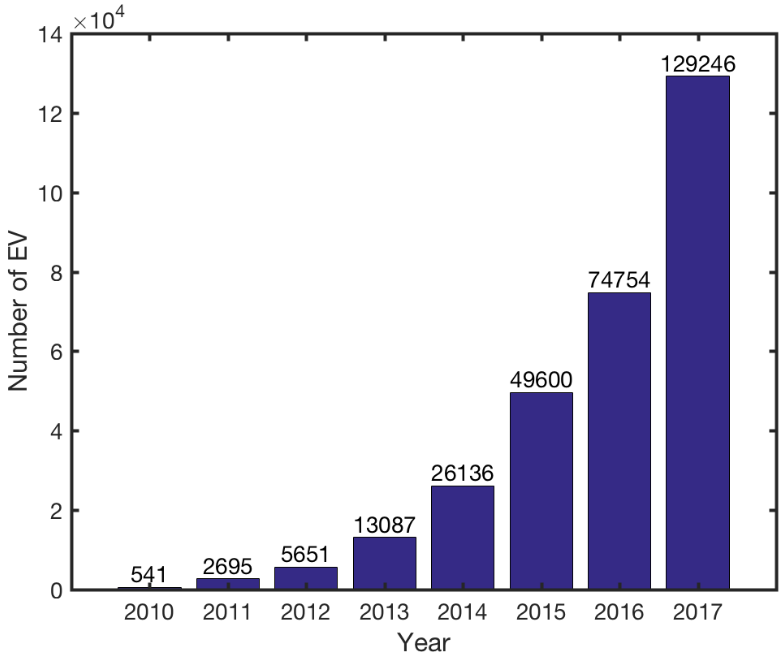

Figure 5.19: Cumulative registration of plug-in electric vehicles in Germany since 2010 [63]

The numbers of EV that were taken for the scenario analysis are then determined and list in Table 5.4.

Table 5.4: The number of EV for each scenario in Germany

Scenario	**EV number total**	**EV number per household**
EV number 2016	74 754	0.014
EV number 2017	129 246	0.025
2% market share	900 000	0.174

Based on these scenarios, we performed the case studies and the results are shown by Figure 5.20. All the business cases reported profits, especially the cases where frequency control markets were coupled. Furthermore, as we seen from the charts, the drastic growth of EVs was reflected on the growth of EV2G market potential from 2016 to 2017, and there are still much more growth space till the scenario of 2% EV market share. However, it shall be noticed that our analysis has overlooked some factors which could make the business less profitable as shown here. The main issue is that we use a determinate approach to simulate the frequency control signal and EV driving behaviors which eliminated the risks of failing to deliver the frequency control services as planned. Alipour *et. al.*[11] made a study on EV2G for frequency control services with a stochastic approach. It was

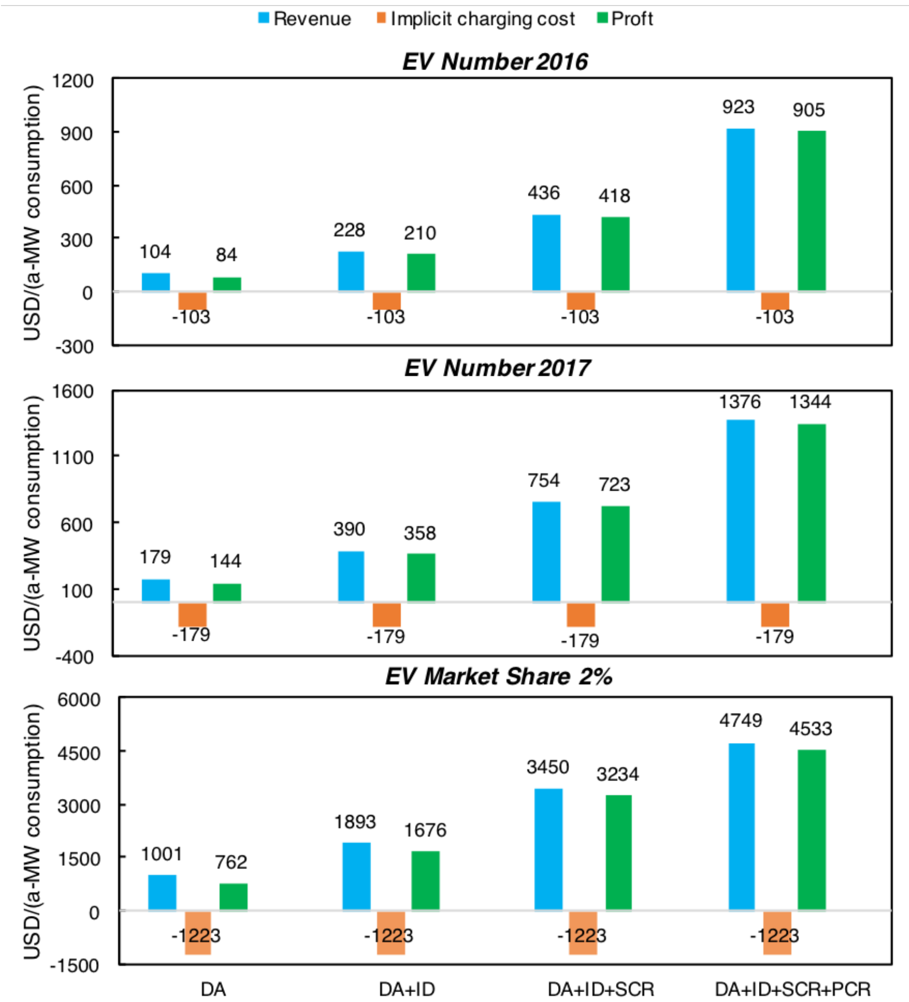

Figure 5.20: Market size and profitability of EV2G in Germany electricity markets

found in a case where a profit of 7980 USD was expected, the conditional value-at-risk was 5720 USD, indicating the risking nature of such a business. In the outlook of this thesis, we proposed a stochastic method by using Markov chain to simulate the uncertain driving behavior of EVs and then the estimation of risk can be conducted. Nonetheless, while quantitative risk assessment against uncertainty is necessary for designing a specific project, it is beyond the focus of a study understanding the whole market value so is not included in our study. Besides, the battery degradation incured by EV driving was not included here while in reality it would be a challenging issue to account the degradation caused by providing EV2G services separately from driving. Finally, implementing EV2G for frequency control is not a mature technology due to its complexity[64][65][66][67], which implies a high

Table 5.5: The number of EV for each scenario in PJM

Scenario	EV number total	EV number per household
EV number 2016	43 713	0.014
EV number 2017	75 578	0.025
2% market share	526 290	0.174

research and development cost.

It is also worthwhile to note that while the number of EVs (0.9 million) in the scenario of "2% Market Share" has reached the edge of the affordable level (1 million) for the grid, revenues are significantly smaller than the maximum potential revenues derived in the case studies of ESSs. The shares of maximum achievable revenue by EV2G to the total market potential by generic ESS were between 25%-50% among different cases. This reveals that constrained by the limitations discussed above, EV2G will not be able fully cover the needs for flexibility by its own, even on a aggregated system level without considering the distributed manners. Other types of flexibility would still be necessary to complement the demands for flexibility in scenarios with high EV penetrations.

EV2G in PJM

Similar studies are performed in PJM power markets. Since the geographic coverage of PJM is not strictly corresponding to the administrative divisions, it becomes a extremely sophisticated task to get the official number of EVs in PJM with the public data. Therefore, we projected the number in Germany to PJM by their ratio of household number. That means, in the corresponding scenarios, the EV ownership per household is identical in Germany and PJM. We took this approach to make an indication of the market value, which however shall be noticed with caution that it may deviate from real conditions. Table 5.5 shows the number of EV in each scenario.

With these numbers of EV, no generation shortage was observed, expect for only one week in the scenario of 2% EV market share. The results in that week were discarded, i.e. no operations and thus no revenues in that week. This accounts for approximately 2% of the time in a year so the impact on final results shall be negligible.

Figure 5.21 summarizes the results of cases in PJM. Compared the results in Germany markets, it can be found that while profits in energy-only cases are similar, the profits with frequency regulation are much higher in PJM than the Germany, which again reveals the adversity against flexibility resources in Germany frequency control markets.

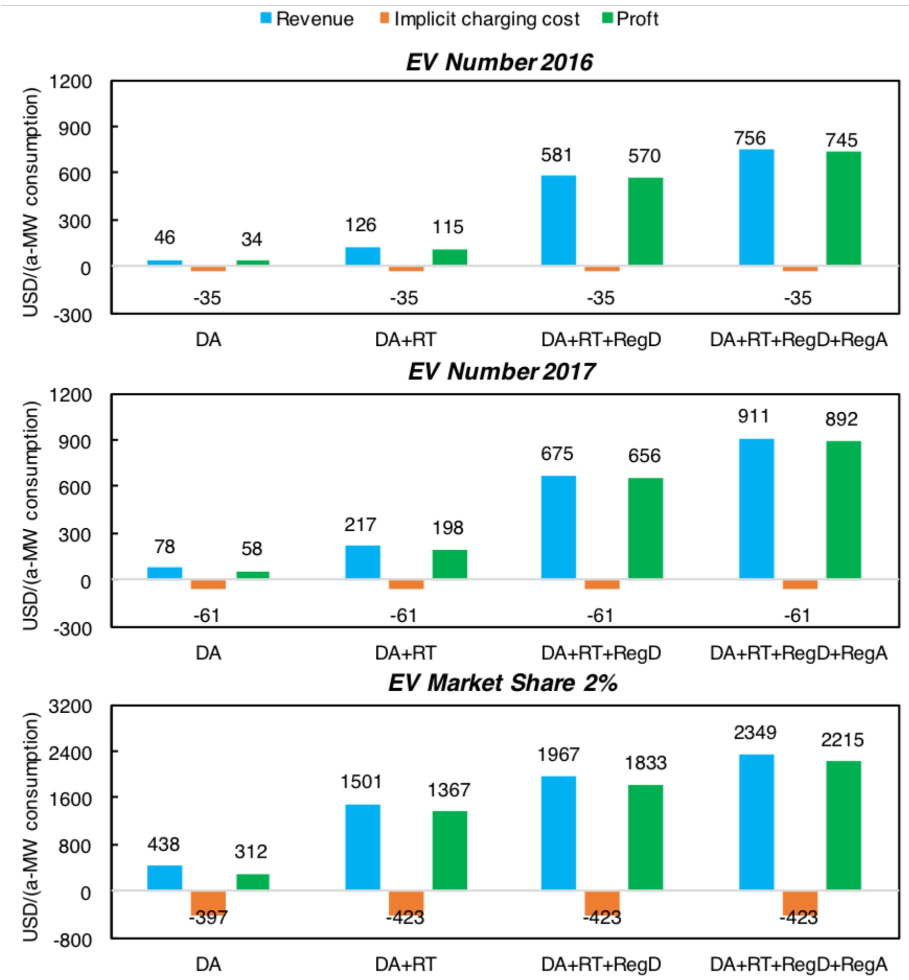

Figure 5.21: Market size and profitability of EV2G in PJM Electricity markets

EV2G in NSW:

Using the same methodology as in PJM, scenarios are established by taking the identical EV numbers per household, as is shown by Table 5.6.

Table 5.6: The number of EV for each scenario in NSW

Scenario	EV number total	EV number per household
EV number 2016	4849	0.014
EV number 2017	8383	0.025
2% market share	58 377	0.174

Figure 5.22 presents the results of three scenarios in NSW's real-time energy market. Although the size of EV fleet is merely 6.5% of that in

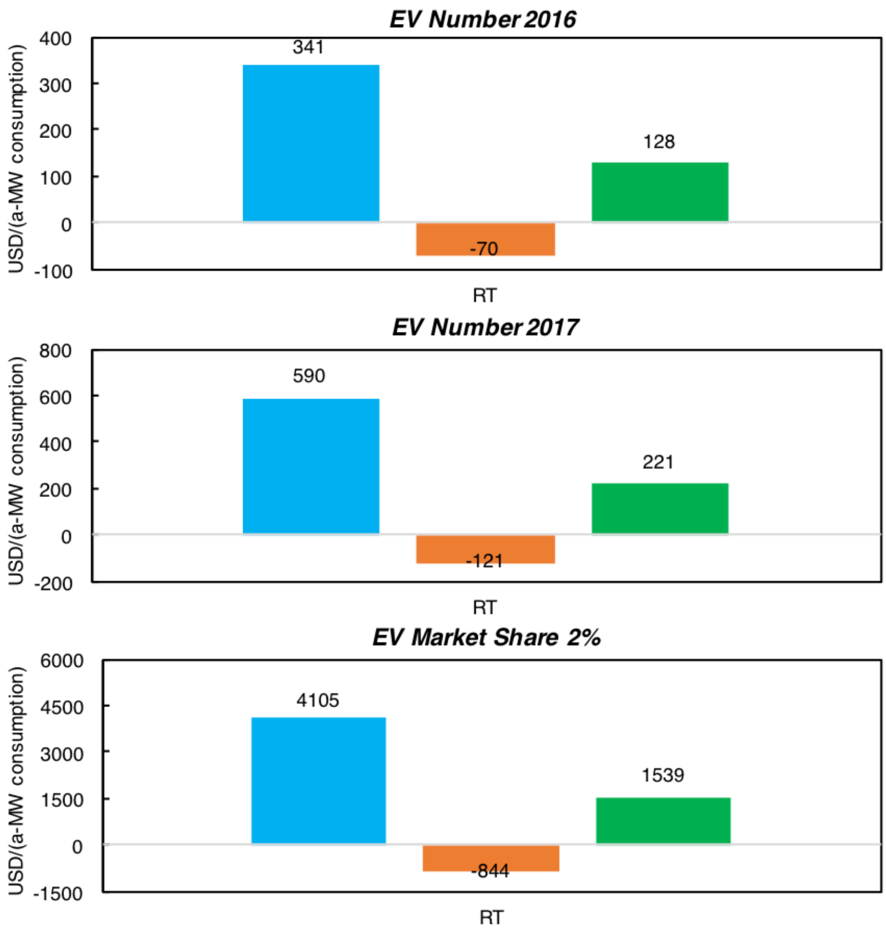

Figure 5.22: Market size and profitability of EV2G in NSW Electricity markets

Germany and 11.1% of that in PJM. The market sizes are generally on the same scale as the other two markets. The revenue per EV of around 560 USD/a and profit per EV of about 365 USD/a are significantly higher than other geographies, as a result of the price volatility in NSW's real-time market discussed previously. High unit return provides more incentives of the end-users to participate in the EV2G program, which makes the business more realizable.

Besides, it can be noticed the overall market size even in the last scenario where we see a revenue potential of 32.8 USD/a accounts for a small portion of the total arbitrage potential in NSW's real-time market revealed in the section for generic ESSs, leaving a vast space for other technologies.

Conclusion

5.2.3 Impact analysis of changing market conditions

Model setup and validation

As is introduced in Section 4.2.3, the market simulation module was designed to generate price scenarios with changed market conditions so that we can analyze the future trend of market value by understanding potential impacts of certain key factors.

The module is developed using the methodology in Section 4.2.3 and based on day-ahead market and generation data in Germany in 2016.

First of all, the data of Germany day-ahead price and volume were collected and shown as Figure 5.23.

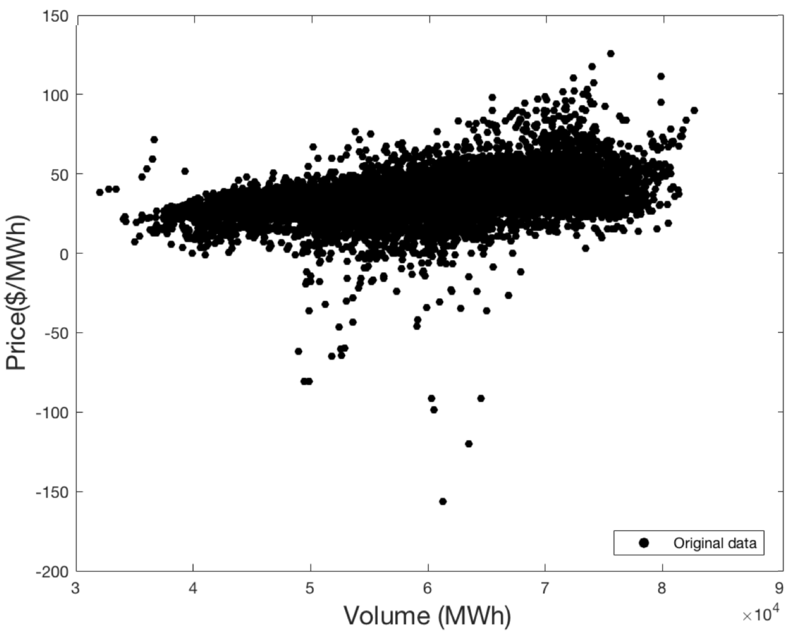

Figure 5.23: Germany day-ahead price-volume data in 2016

The pattern of merit-order effect is not clearly recognizable from the original data mainly due to the disturbs of variable renewable generation which has raised significantly in past years. This prevents us from directly applying merit-order models developed by previous studies[9][27]. Therefore, we applied the algorithm described in Section 4.2.3 which take into account the renewable generation and bounded flexibility of conventional generations. Figure 5.24 shows the transformed pattern of data where a clearer merit-effect is identifiable. Figure 5.25 projects the classification to the original data distribution and it can be seen that the algorithm has successfully separated the data points where the price was driven to be higher or lower than average level due to the uplift effects introduced in 4.2.3.

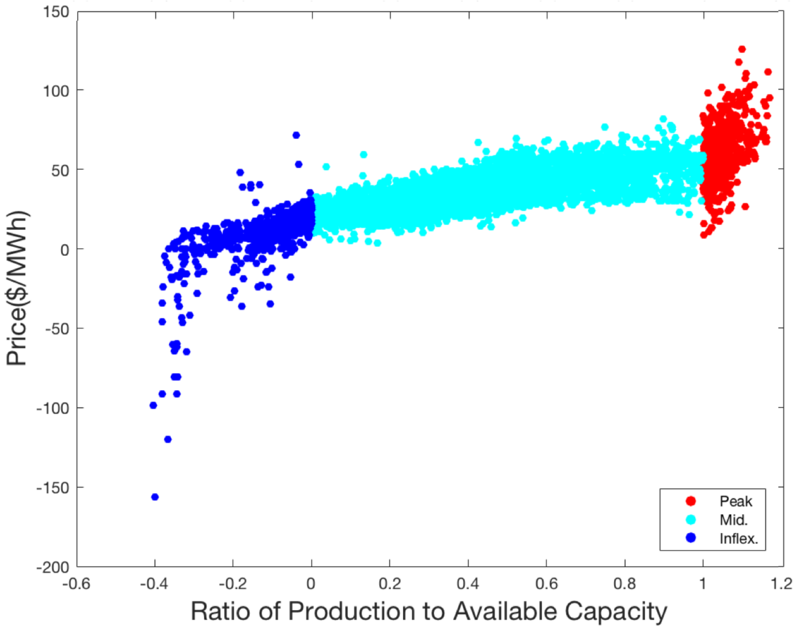

Figure 5.24: Transformed pattern of Germany day-ahead price-volume data in 2016

Thereafter, we fitted the transformed data pattern with the piece-wise function defined by (4.19). The estimated parameters are listed in Table 5.7. The fitted merit-order curve is illustrated by Figure 5.26 and distribution of errors between the fitted price and actual price is shown by Figure 5.27.

Table 5.7: Parameters of the merit-order model

Class	Parameters		
	a	b	c
Inflex.	17.05	-1.49	-12.35
Mid.	48.66	16.40	
	38.04	20.12	
	16.37	34.20	
Peak	-194.95	491.46	-0.69

We simulated the day-ahead price using this merit-order model and compared to the actual market data. It can seen from Figure 5.26-5.27 that while the fitted merit-order price shows a good fitness to the actual price in terms of general trend, the stochastic movements of the price are eliminated. Merely with the merit-order model, a smoothed curve of price time-series

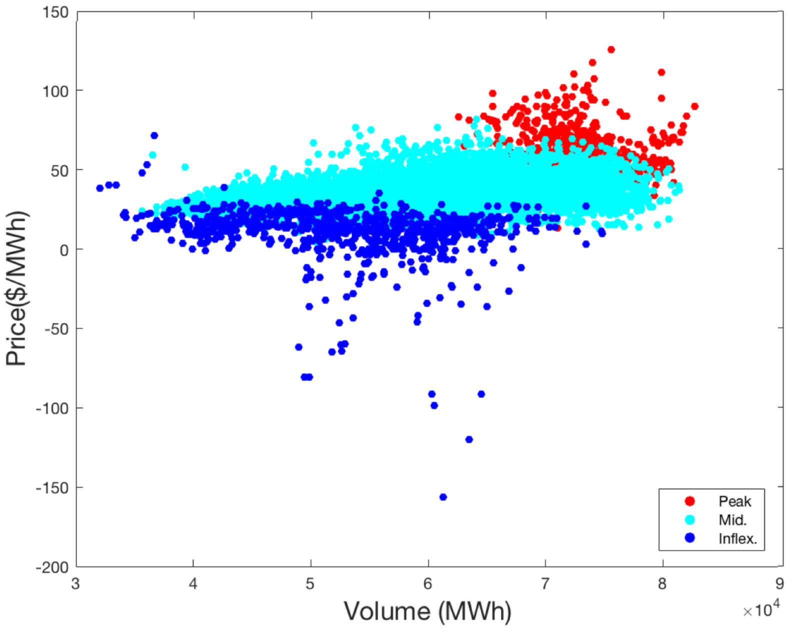

Figure 5.25: Classification of Germany day-ahead price-volume data in 2016

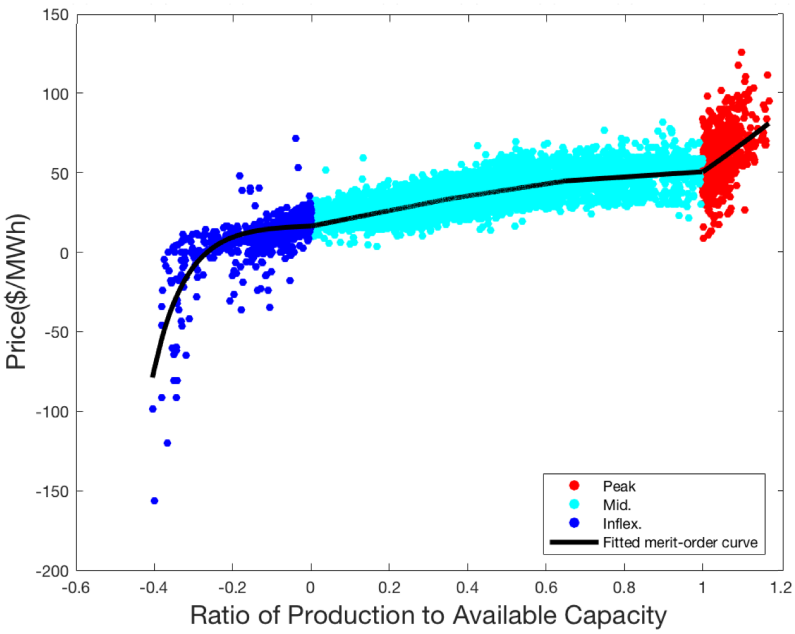

Figure 5.26: Fitted merit-order curve with Germany day-ahead price-volume data in 2016

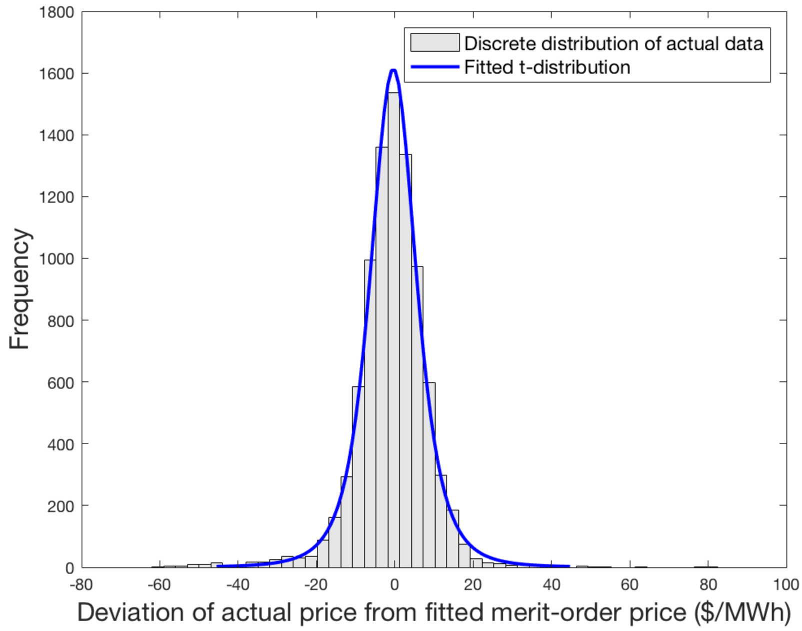

Figure 5.27: Distribution of errors between fitted merit-order price and actual price

would be generated where the drastic jumps of price cannot be captured, as is demonstrated by Figure 5.28.

Unlike studies on valuation of a conventional generation resources where such a merit-order model may suffice, the elimination of stochastic price movement would reduce the value of arbitrage greatly as is shown by Figure 5.29. This shall be understood intuitively as arbitrage activities pick the price differences among different trading slots and less volatile price movements would certainly affect the value creation of arbitrage.

Table 5.8: Parameters of the stochastic price movement of SARMA models

SARMA parameters	
$\phi_1 = 1.811$	$\theta_1 = -1.063$
$\phi_2 = -0.813$	$\theta_{24} = 0.692$
$\phi_{24} = 0.090$	$\theta_{168} = -0.600$
$\phi_{168} = 0.692$	

Therefore, a seasonal auto-regressed moving-average (SARMA) model as is described in 4.2.3 is applied to simulate the stochastic components of the price. The estimated parameters of the SARMA model based on the error signal characterized by5.27 is listed in Table 5.8. Thereafter, we conducted Monte-Carlo simulations and generated a number of scenarios of

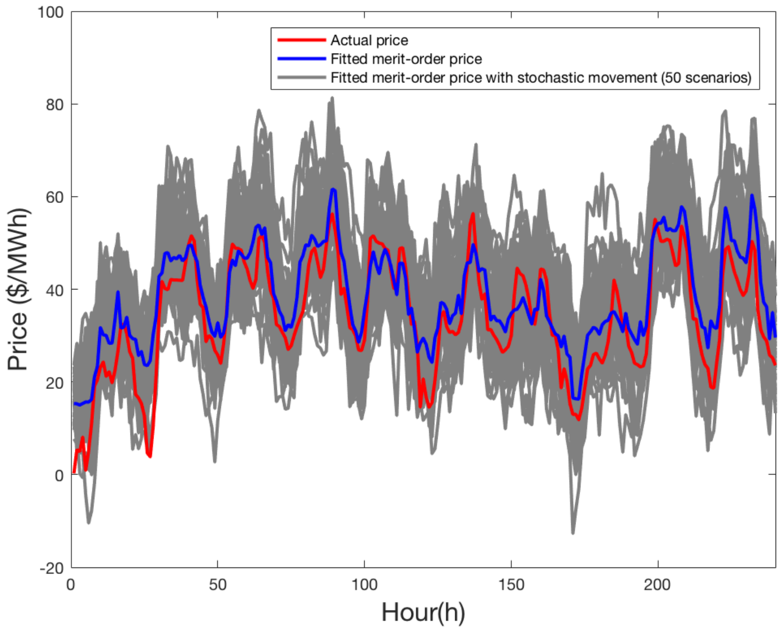

Figure 5.28: Generated price scenarios

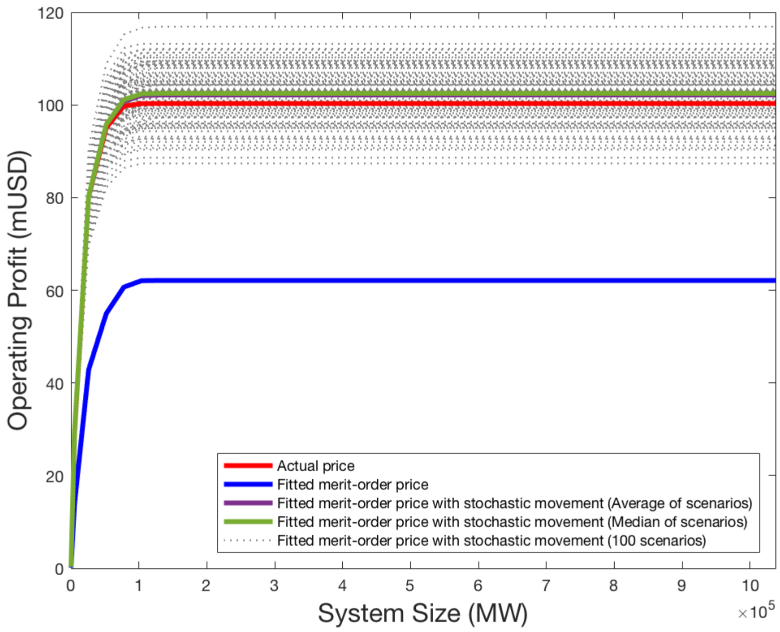

Figure 5.29: The revenue with different price scenarios

the stochastic parts of price which are then added to the determinate trends calculated by the merit-order model. The final simulated price scenarios are illustrated by the grey lines in Figure 5.28. Using these generated price profiles, we calculated the revenue for 100 scenarios and compare the average and median value to the result obtained with actual price signal, which shew perfect fitness in Figure 5.29. There are no significant differences between the average and median value observed, but for robustness and avoiding effects of outliers, we would use the median value as the simulated result for experiments in proceeding sections.

Impact of renewable penetration

Impact of increasing flexibility

5.2.4 Sensitivity analysis

Limited predictability

Database

Locational price

Sensitivity analysis of other parameters

Chapter 6

Conclusions and outlook

Appendix A

Accounting rules and electricity market data prepration

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