ETH
Eidgenössische Technische Hochschule Zürich
Swiss Federal Institute of Technology Zurich

PSL Power Systems Laboratory

Xingliang Fang

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

Master Thesis
PSL1226

EEH – Power Systems Laboratory, ETH Zurich
Corporate Strategy Office , Landis+Gyr

Examiner: Prof. Dr. Gabriela Hug
Supervisor: Dr. Donnacha Daly (Landis+Gyr), Jun Xing Chin

Zurich, March 8, 2018

Contents

Chapter 1

Introduction

1.1 Background

Background

Definition of flexibility

The challenges due to renewable penetration:

Traditional flexiblity from supply-side has limitations due to

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

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

Uncapping the potential

1.2 Technologies: options for system flexibility provision

- supply-side flexibility

  Conventional power plant response

  Curtailment of variable renewable

- Energy Storage System (ESS)

  Battery Energy Storage System (BESS)

  Pumped Hydro Energy Storage (PHES)

  Compressed Air Energy Storage (CAES)

Flywheel

- Demand Response (DR)
- Other

  Electric Vehicle to Grid (V2G)

  Electricity to Heat (E2H)

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

1.3 Applications, benefits and business models

1.3.1 In liberalized market

Needs of different plyaers

Player * Market * Application

Energy Markets

Ancillary Service Markets

1.3.2 In vertically integrated market

1.4 Scope and research questions

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

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

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

-

The goal of this thesis is to:

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

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

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

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

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

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

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

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

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

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

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

Chapter 2

Literature Review

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

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

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

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

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

2.1 Purpose and stakeholder

2.2 Modelling methodology

2.2.1 Overview

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

2.2.2 Engineering model

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

2.2.3 System model

2.3 Affecting factor

2.3.1 Techno-economic characteristics of power system

Generation

Generation mix (Renewable integration) Fuel Prices

Climate and weather

Transmission

Grid topology Transmission capacity

Consumption

Merit-order model

[1]

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

2.3.2 Statistic model

[11]

2.3.3 Perfect forecast

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

2.3.4 Power market degisn and policy regulation

Player and competitive landscape

Renewable Support Scheme

Power Market Design

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

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

Balancing market design [17] [18]

Ownership and dispatch

Direct policy support

Capacity market Feed-in premium or tariff Other program

2.4 Value of results for reference

2.4.1 Demand for flexiblity in power system

2.4.2 Profitability of flexibility solutions

Chapter 3

Power Markets and The Role of Flexiblity Management

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

3.1 Power market frameworks

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

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

3.1.1 General stucture of power markets

3.1.2 Key attributes of power market stucture

3.2 Overview

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

3.2.1 Energy market

3.2.2 Ancillary service market

3.2.3 Capacity remuneartion mechanism

3.3 Power market design and structure

3.3.1 PJM

3.3.2 Germany

3.3.3 Australia

3.4 Regulatory and market framework for flexibility resourses

(Placeholder)

(Placeholder)

(Placeholder)

(Placeholder)

(Placeholder)

(Placeholder)

(Placeholder)

(Placeholder)

(Placeholder)

(Placeholder)

(Placeholder)

(Placeholder)

(Placeholder)

(Placeholder)

(Placeholder)

(Placeholder)

(Placeholder)

(Placeholder)

(Placeholder)

(Placeholder)

(Placeholder)

(Placeholder)

(Placeholder)

(Placeholder)

(Placeholder)

(Placeholder)

(Placeholder)

(Placeholder)

(Placeholder)

(Placeholder)

(Placeholder)

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

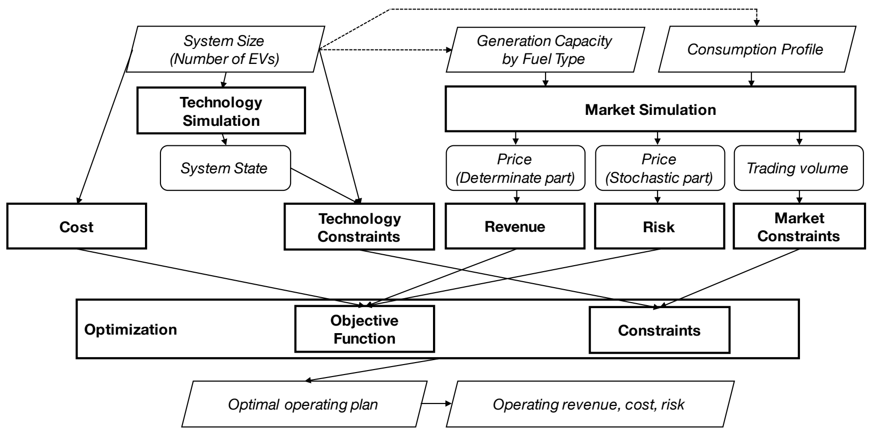

Figure 4.1: Flow chart of the techno-economic model

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;

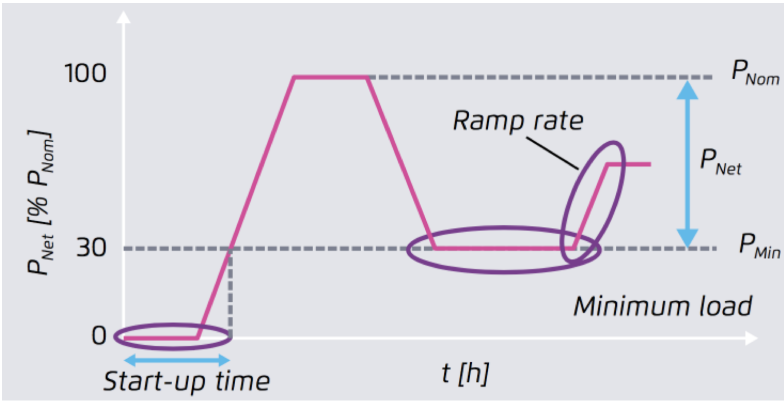

Figure 4.2: Qualitative representation of key flexibility parameters of a power plant[29]

- Ramp rate: the speed of adjusting output;
- Start-up time: the time required to attain stable operation from stand-still

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 stand-still 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

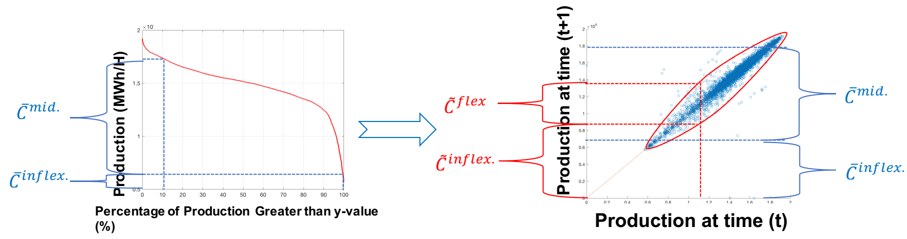

Figure 4.3: Schematic illustration of determining bounded flexibility for limited flexible generations

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

$$\left[\Gamma^d \quad | \quad \Gamma^c \quad | \quad \Gamma^r\right] X \leq \boldsymbol{b} \tag{4.24}$$

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).

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

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

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).

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

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

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

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

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 storages:

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

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

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

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

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

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

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

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

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

which can be reformulated as:

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

where

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

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

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:

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

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

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

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

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

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

The constraints of storage are formulated as:

$$-\boldsymbol{h}\,X \leq \boldsymbol{h}_0 \tag{4.53}$$

$$\boldsymbol{h}\,X \leq \overline{S} - \boldsymbol{h}_0 \tag{4.54}$$

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

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

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

$$\overline{R} = \overline{r}N \tag{4.55}$$

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 Accounting rules and electricity market data preparation

5.3 Quantitative studies and results

5.3.1 Value of markets with current market conditions

We first examined the value of markets under current market conditions, i.e. based on historical observations without involving the market simulation module (Section 4.2.3). The impact of possible changes in market conditions such as renewable penetration will be discussed later in Section 5.3.2.

The electricity market data that were taken for all case studies in this section corresponds to the actual market data from January 1st 2016 to December 31st 2016 and were pre-processed according to different accounting rules in different geographies as is described in Section 5.2.

For cost determinations, we applied two scenarios, i.e. present scenario and future scenario with reduced costs, primarily based on findings and forecasts by the International Renewable Energy Agency[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 and predicted to decrease by up to 60% by 2030. 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 5.3.1.

Table 5.1: Parameters for cost calculation

Items	**Present Cost**	**Reduced Cost**
Energy cost coefficient, C^s $\$/kWh$	350	140
Power cost coefficient, C^s $\$/kW$	0	0
Technology cost, $	0	0
Replacement cost coefficient, C^s $\$/kWh$	150	60
Designed life time, *year*	10	
Operating life time, *FCE*	6000	
Discount rate, %	10	

It shall be pointed out 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 as BESS. 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].

Then simulation is performed to get EV driving profiles. The simulations 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 vehilces, 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.

The criteria to evaluate the system performance are different between ESS and EV2G. For ESS, these criteria include

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

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 shall be added back for final profit calculation. Therefore, the criteria are altered as:

- **Explicit Revenue:** the total explicit revenue from electricity markets calculated as Equation (4.1)

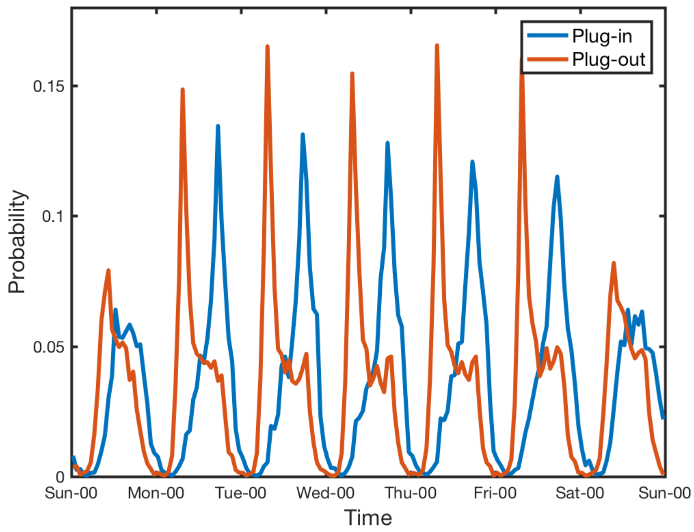

Figure 5.1: Probability of EV plug-in/ plug-out

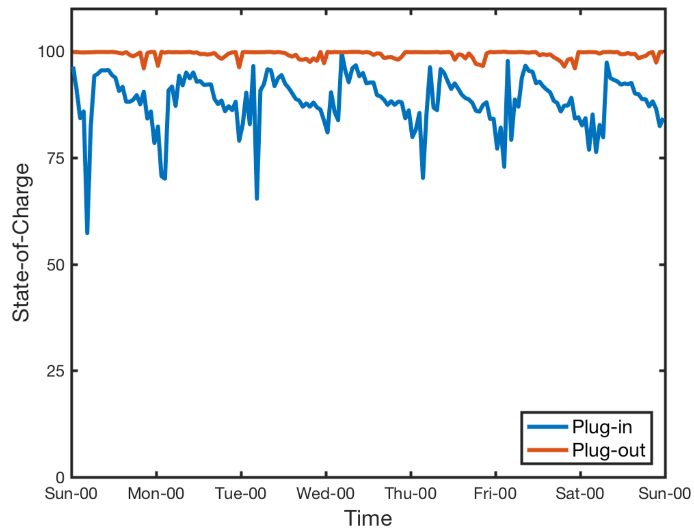

Figure 5.2: Average SoC of EV when plug-in/ plug-out

- **Implicit Charging Cost**: the cost of energy compensation for EV driving demands, calculated as the total energy consumption multiplied by average price over the span of one operational cycle

- **Total Revenue:** the aggregation of explicit revenue and add-back of implicit charging cost

- **Profit:** total revenue net of operational costs. The investments on technology is made to be zero as is discussed at the beginning of this section

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 market size and profitability of ESS, we evaluated the system performance with different total sizes. Thereafter, we would select and analyze 4 key states corresponding to 4 scenarios as following:

- "**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**".

  This scenario can present a reference of the maximum market potential to the technology vendors as they might be able to develop technologies whose costs are lower than what we calculated in the case studies.

- "**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 profits either drop monotonically or decrease after an initial rise, this state is obtained when the profit falls to be 0.

  Since our case studies applied idealized conditions, the results are viewed as upper bounds of the actual market value. Without revolutionary innovations on technologies, comparing values derived in this scenario to the current market data would offer implications to the technology vendors whether the market is saturated or not.

- "**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.

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

  We would also present the values in per unit for this scenario so that the maximum potential return per unit system can be understood more intuitively.

The 4 scenarios can be illustrated by Figure 5.3 using the results from a case of making arbitrage in day-ahead, real time energy markets and simultaneous delivering regulation services in PJM electricity markets.

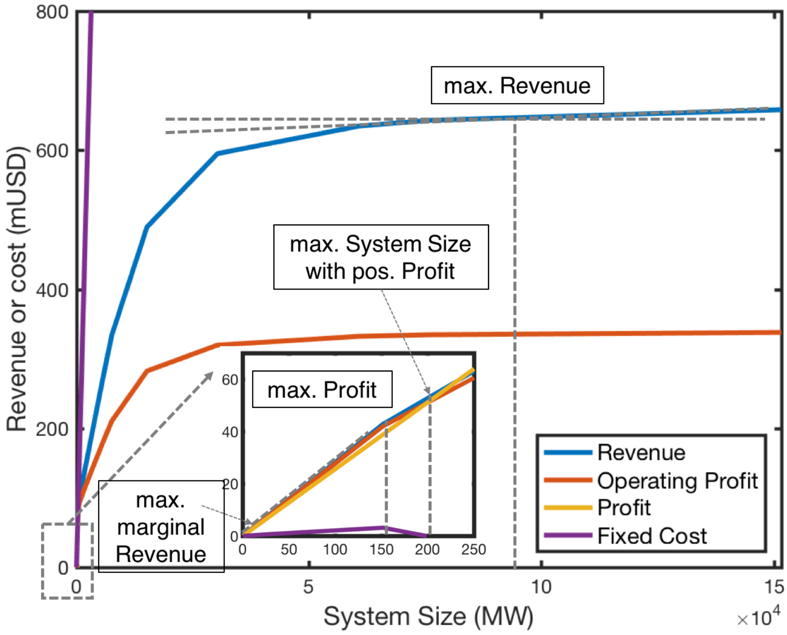

Figure 5.3: Graphic illustration of 4 scenarios

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.

Finally, in order to make cross-regional comparison, we have aligned the currencies to USD. The currency exchange rate is determined using the data as of January 1st 2018, when 1 EUR is equal to 1.2 USD and 1 AUD is equal to 0.79 USD.

Market size and profitability of ESS in Germany

Figure 5.4 summarizes the market size and profitability of all cases for ESSs in Germany electricity markets.

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. It can be noticed that using BESSs for self-balancing is more economic viable than selling frequency control

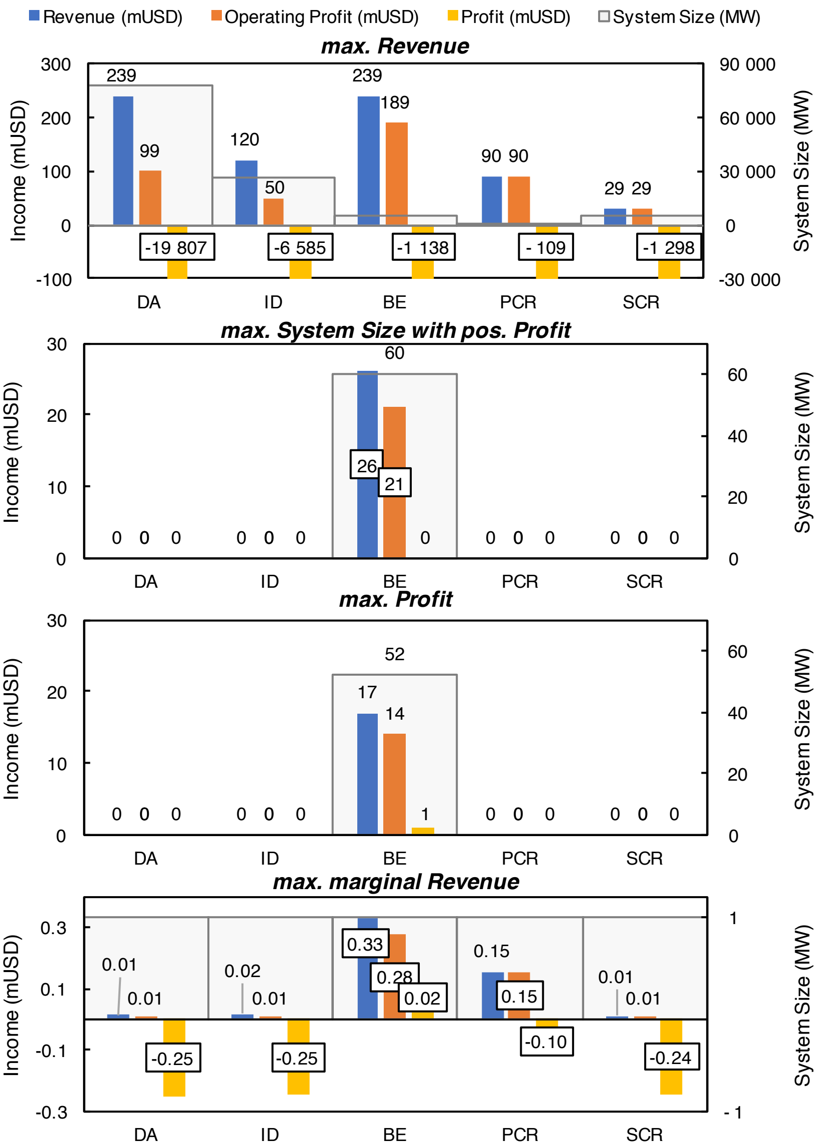

Figure 5.4: Market Size and Profitability of ESS in Germany Electricity Markets

service to TSOs. Under same system size, the revenue from self-balance is significantly higher than from selling frequency control products, while theoretically these two values shall be symmetric as the balancing energy charges are designed to recover the costs of purchasing frequency control services. This implies that the current design of frequency control markets is not economically efficient 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.

Although systems with optimal sizes and optimized operations can generate profits in balancing energy market, it is challenging to determine the optimal size and operational plan of a specific project in practice. If a system is designed to large enough and tackle almost all imbalance events, it corresponds to a situation as the "max. Revenue" scenario where we see negative profits. On the other hand, if the system's size is limited, it is not practically feasible to find the best operational plans using optimization. As is discussed in Section 5.2, the balancing energy price, reBAP, is calculated *ex-post* and highly volatile, hardly predictable.

As a conclusion on providing balancing services, although the BESSs can contribute to imbalance settlement in certain conditions where the avoided costs are higher than investments in BESS infrastructure, there exist no market frameworks so far to make it feasible for the market participates. Players of BESSs face either lack of information transparency in the balancing energy market or unfavorable market rules in the frequency control market.

Regarding arbitrages value in energy market, the losses are about 10-20 times of the revenue, even in the scenario of maximum unit return. 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 the technology vendors are able to enable similar functions as BESS using technology with smaller capital costs like certain types of DR, it is still possible to make profits from arbitrage in energy market.

As has been discussed qualitatively, in order to increase the profitability, we may stack operations in day-ahead, intra-day and secondary control reserve for multitasking. Figure 5.5 shows the effects of multitasking.

While there are no significant synergies between day-ahead and intra-day markets, stacking secondary control reserve with these energy marketplaces will significantly improve the unit return as well as the maximum revenue potential. This corresponds to our previous analysis that the issue of non-energy-neutral signals can be tackled by introducing third-party energy for offset. Nonetheless, these two cases with multitasking are still not profitable.

Market size and profitability of ESS in PJM

The results of case studies in PJM power markets are illustrated in Figure 5.6. As we can clearly see, the RegD marketplace that is specially designed for emerging flexible technologies is indeed profitable. By introducing the concept of mileage ratio and implementing energy-neutral signals, the market with a total size of 45 mUSD can be realized by players of flexibility without writing a loss, although the margin is very niche, barely above zero.

Stacking it with the energy market does not significantly improve the

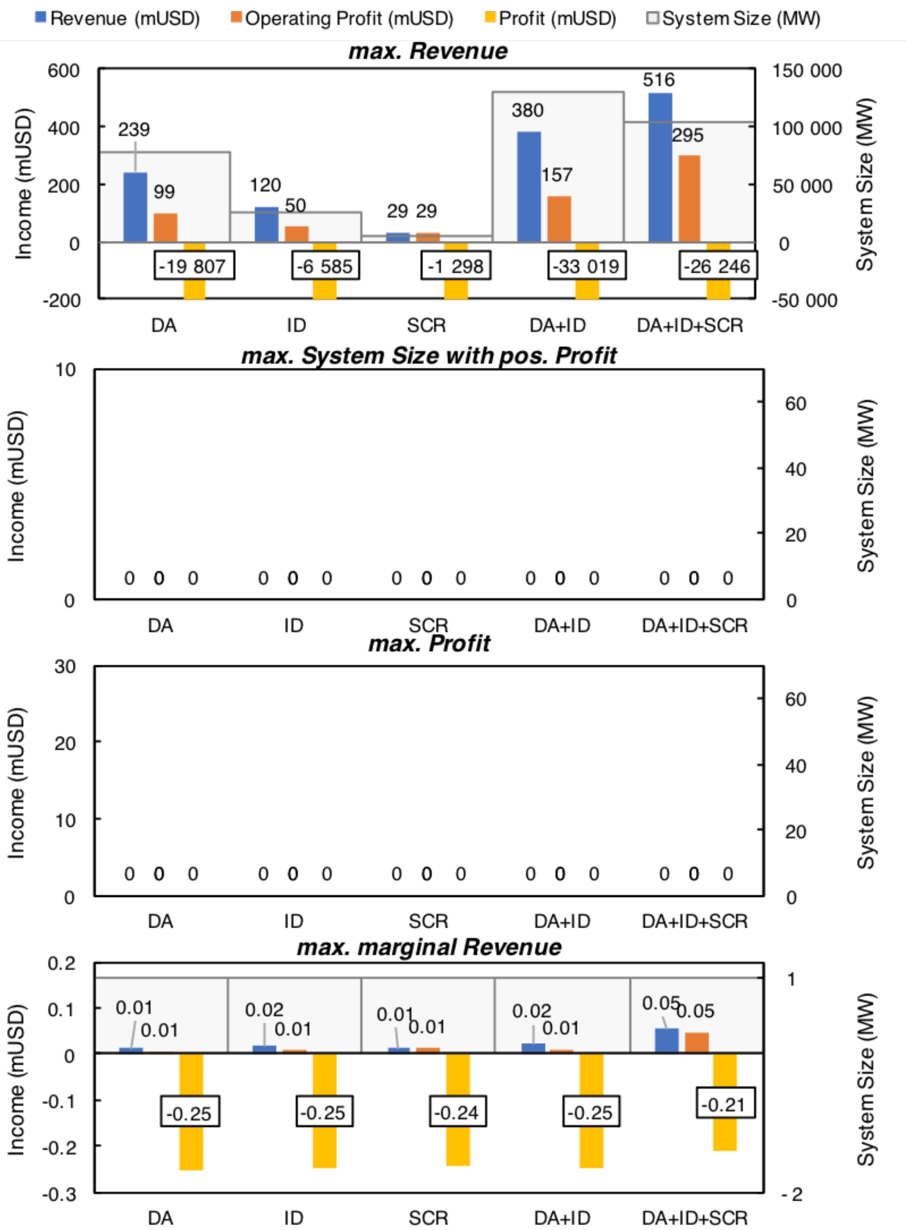

Figure 5.5: Market Size and Profitability of ESS with multitasking in Germany Electricity Markets

profitability. The energy-neutral signals allows a BESS to sustain the provision of RegD service over a period without involving transactions in energy markets. The advantage of multitasking in this case is only to allow the decision makers to have more choices so that they can better schedule their plan by responding to the price trend. PJM allows participates to alter

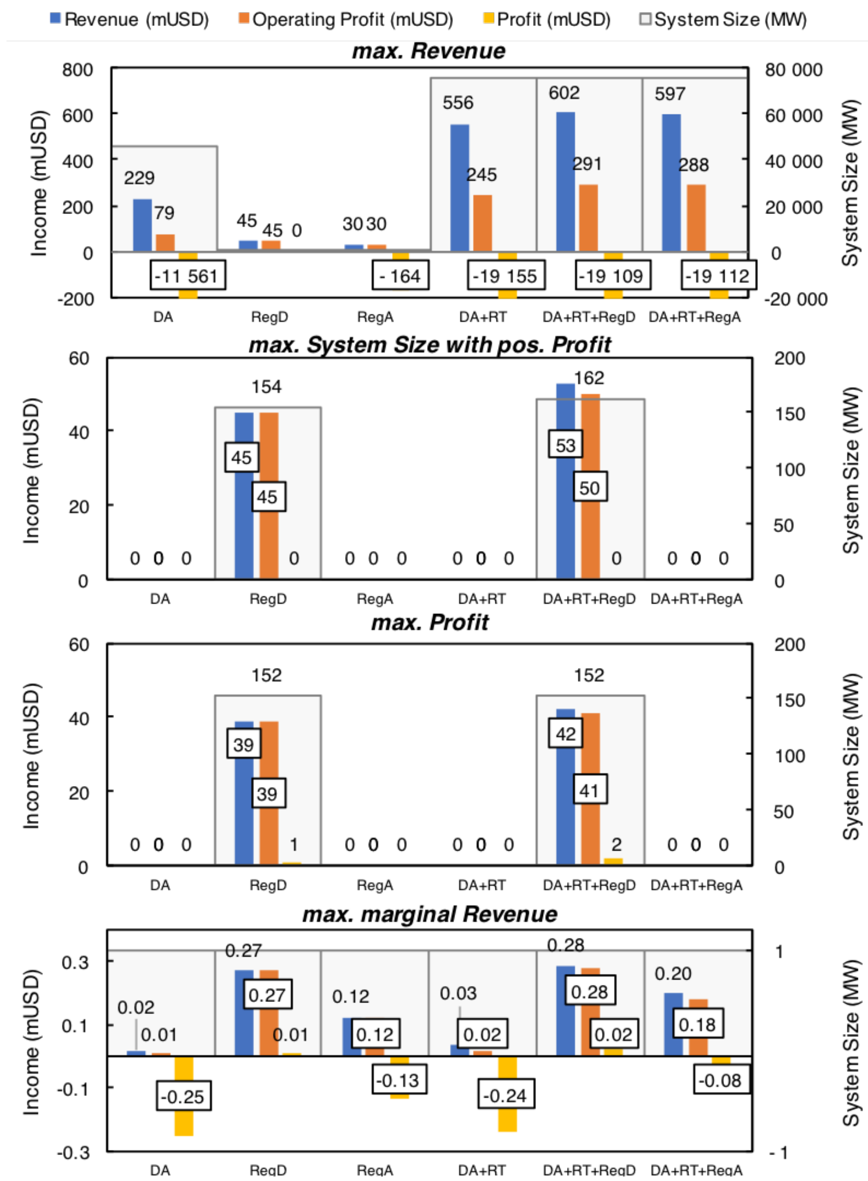

Figure 5.6: Market Size and Profitability of ESS in PJM Electricity Markets

their RegD offers in hourly block which offers additional operational flexibility compared to the arrangement in Germany's frequency control markets. However, as we can see from Figure 5.7, RegD is preferred due to its higher profitability and resources are rarely allocated to deliver day-ahead or real-time energy in the optimized plan.

Apart from RegD market, there are no other profiting opportunities existing in PJM. Even the conventional regulation service RegA will create losses to BESS players.

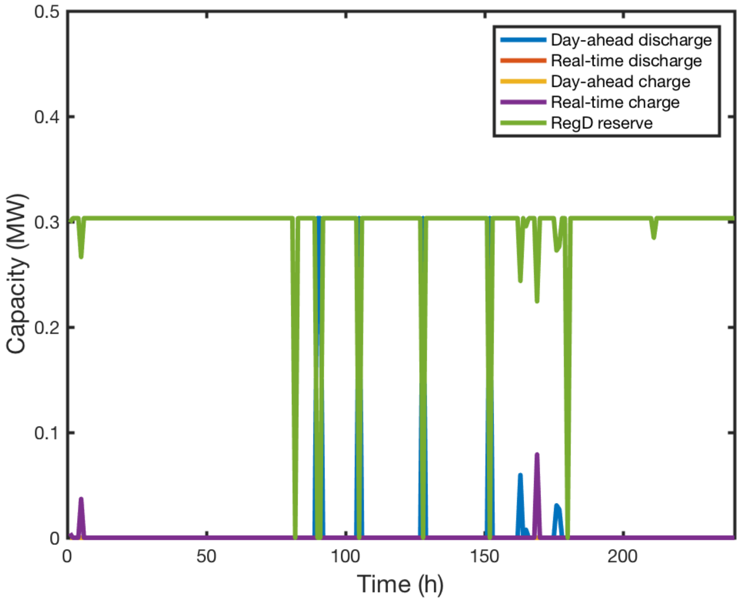

Figure 5.7: A example of operational plan with a 0.3MW battery energy storage system

Arbitrage in the energy market with flexibility through the so-called economic DR program, as is discussed in Section, 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 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.

Market Size and Profitability of ESS in NSW

In New South Wales power markets, we only studied the real-time energy market due to the limitation of data availability. As is shown by Figure 5.8, even though the operating profit per unit is about 6 times the values in the other geographies studied previously, it is still not sufficient to recover the expenses on the battery stocks.

Market Size and Profitability of EV2G in Germany

Implementing EV as a grid resource is not as straightforward as using a generic ESS 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.

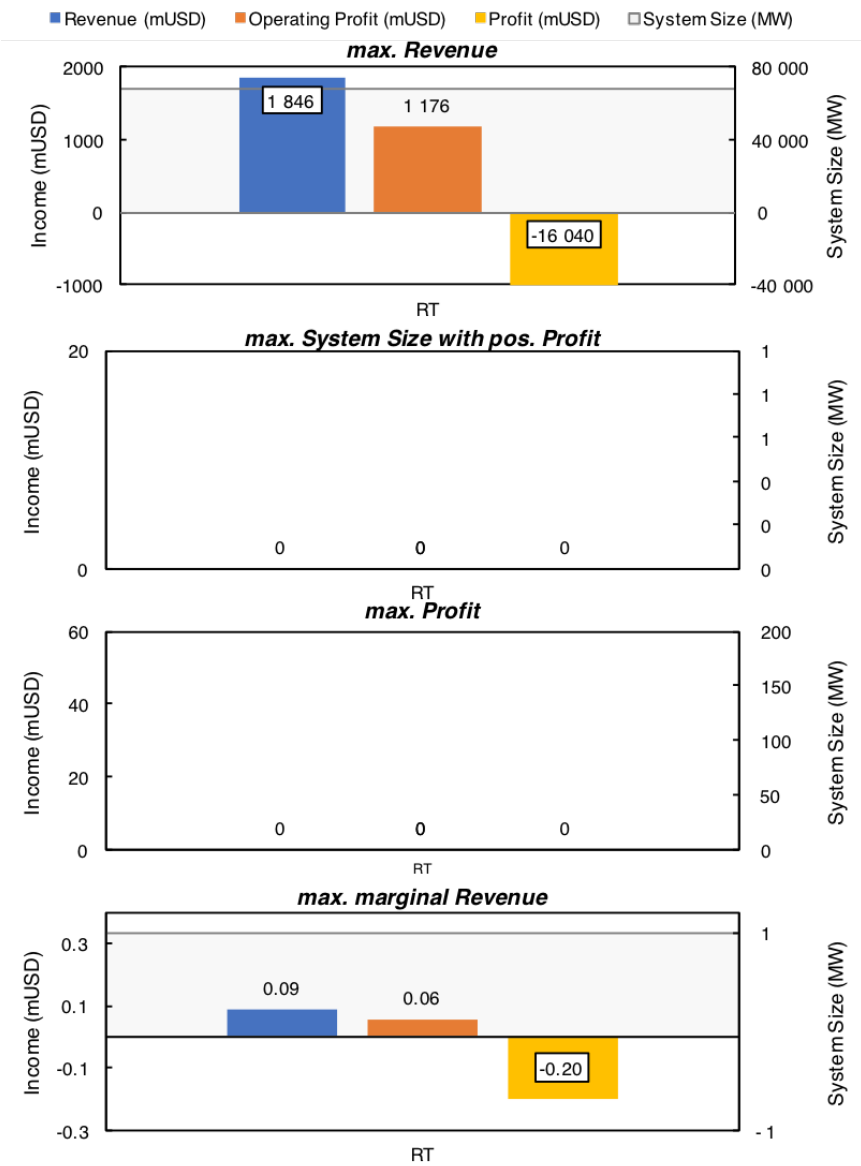

Figure 5.8: Market Size and Profitability of ESS in NSW Electricity Markets

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 with large number of EV fleet, especially the one that we set to restrict the activation of peak generation during non-peak hours. This corresponds to the situation that 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. As is shown by Figure 5.9, when the number of EV is higher than 1 million, it start to stress the electricity supply with present generation fleet.

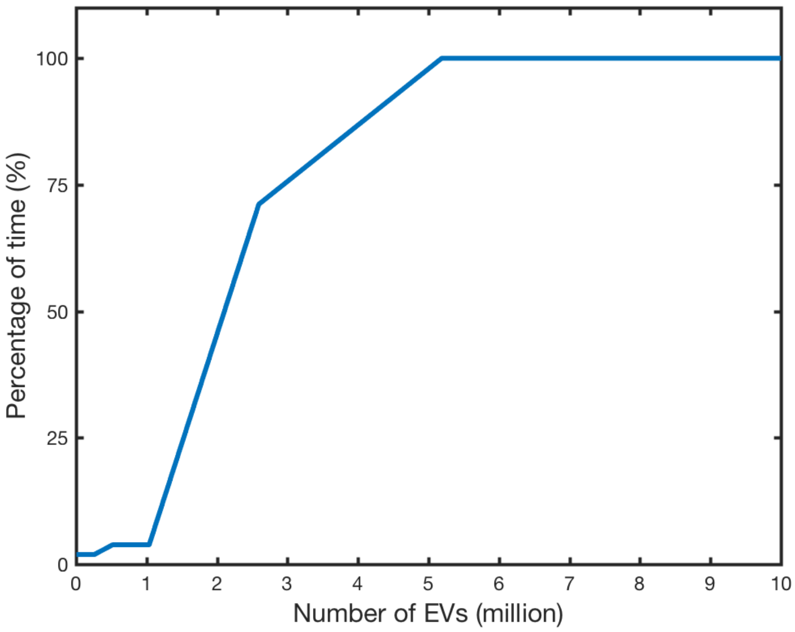

Figure 5.9: Percentage of time when EV charging demand cannot be fulfilled in Germany

This finding implies when there will be 1 million more EVs in Germany compared to the level 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.

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 [56]) i.e. 0.9 million EVs in the future, which is within the 1 million limits discussed above

According to the Federal Motor Transport Authority of Germany (Kraftfahrt-Bundesamtes, KBA)[57], 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 5.10.

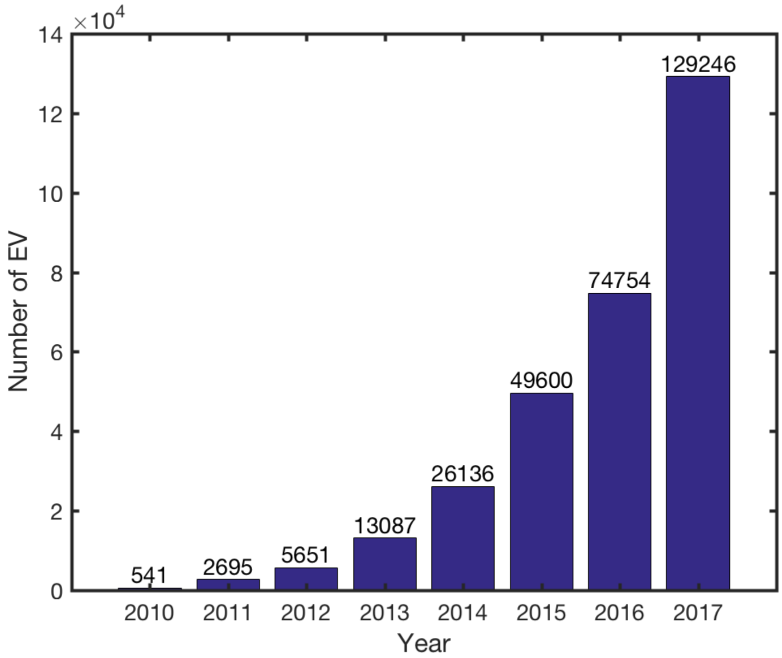

Figure 5.10: Cumulative registration of plug-in electric vehicles in Germany since 2010 [57]

By taking the EV number as 74 754 in 2016 and 129 246 in 2017, we performed the case studies and the results are shown by Figure 5.11. All the business cases reported profits, especially the cases where frequency control markets are coupled. However, it shall be noticed that our analysis has overlooked some factors which could make the business less profitable as they are shown here. One issue is that we use a determinate approach to simulate the 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 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 risk control against uncertainty is necessary for designing a specific project, it is beyond the focus for a study understanding the whole market value so is not included in our study.

Besides, it shall be noticed that implementing EV2G for frequency control is not a mature technology due to its complexity[58][59] [60][61], which implies a high research and development cost for the technology vendors.

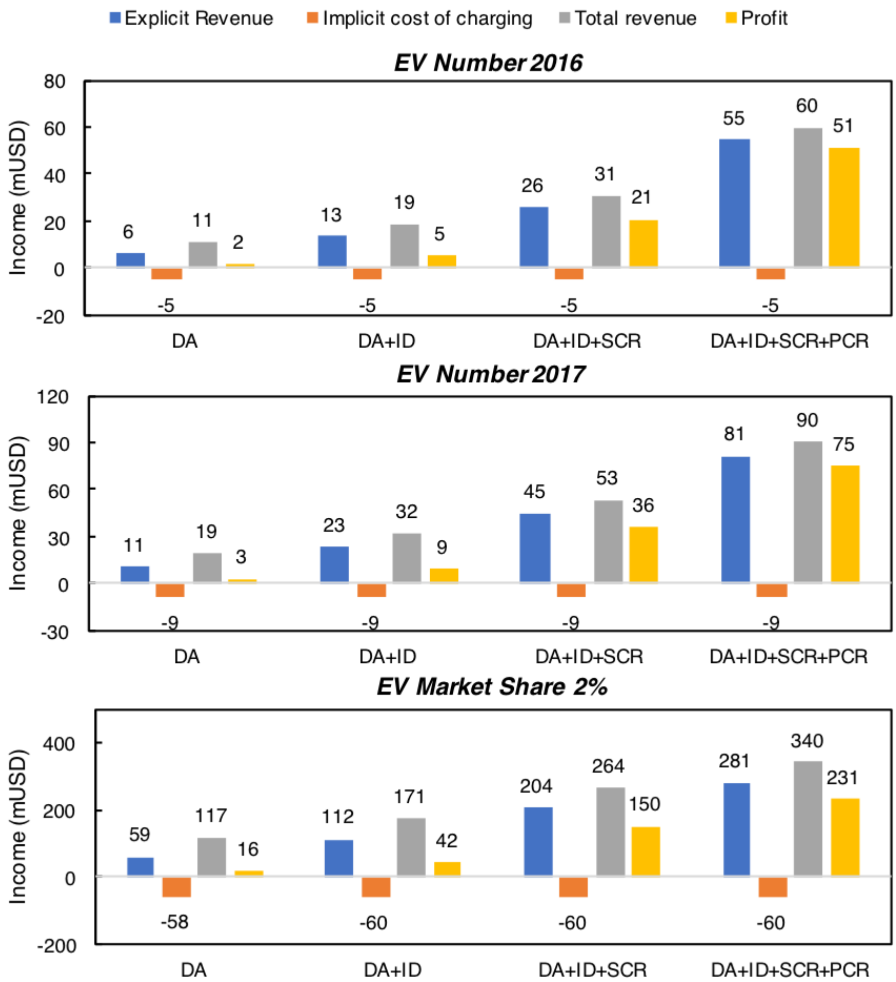

Figure 5.11: Market Size and Profitability of EV2G in PJM Electricity Markets

Market Size and Profitability of EV2G in PJM

We performed the study in PJM power markets. Firstly it is found that which additional 300k EVs, it would gradually fall into supply shortage (Figure 5.12).

Since the geographic coverage of PJM is not strictly corresponding to the administrative divisions, it is a complex task to get the official number of EVs in PJM with the public data. Therefore, we projected the number

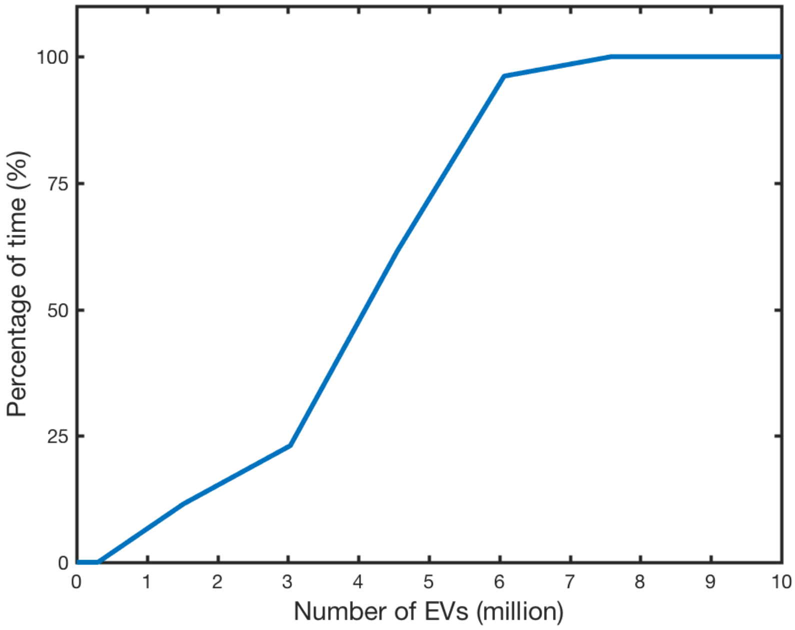

Figure 5.12: Percentage of time when EV charging demand cannot be fulfilled in PJM

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 viewed with caution that it may deviate from real conditions.

Figure 5.13 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 closed, 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.

Market Size and Profitability of EV2G in NSW

(An issue was found related to this case while analyzing the data, so the results will be ready later.)

Contribution of cost reduction

(This subsection will come later. As a short summary, only PCR in Germany and RegA in PJM switched their profitability to be profitable. The other cases of arbitrage that were shown to be unprofitable still lead to losses even with the cost reduced by 60%.)

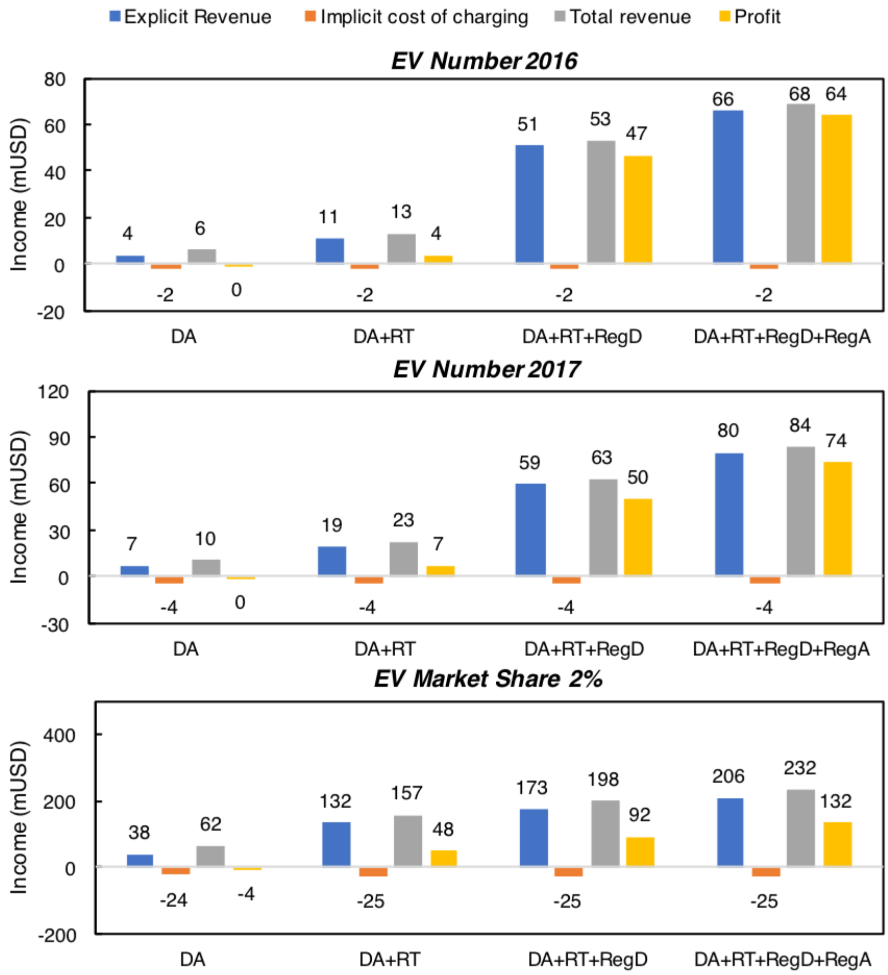

Figure 5.13: Market Size and Profitability of EV2G in PJM Electricity Markets

5.3.2 Impact analysis of changing market conditions

Model 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, or at least the potential impacts of certain key factors.

The module is developed using the methodology in Section 4.2.3. It is trained and validated by day-ahead price and generation data in Germany in 2016.

In order to get the parameters of the model we first collect the Germany day-ahead market in 2016, shown as Figure 5.14.

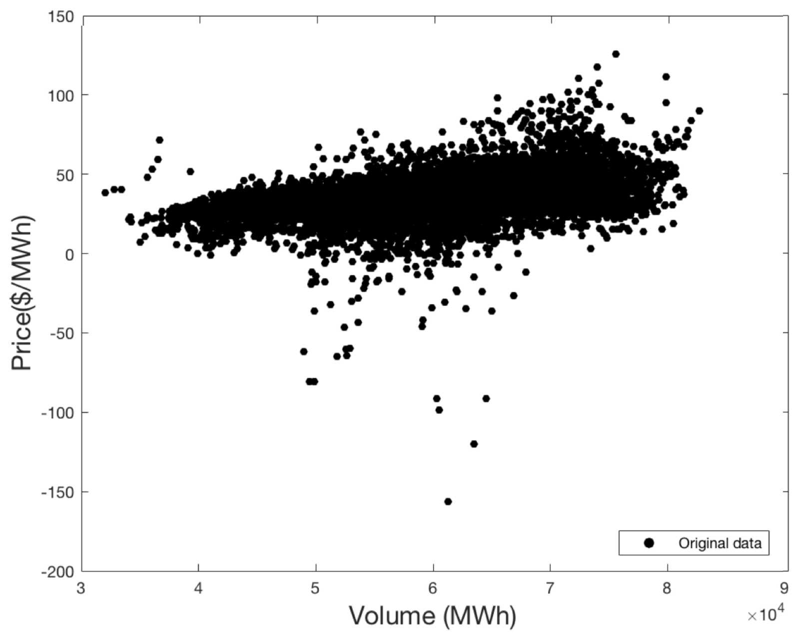

Figure 5.14: Germany day-ahead price-volume data in 2016

It clearly shows that the pattern of merit-order effect is not 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 the 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 5.15 shows the transformed pattern of data where a clearer merit-effect is identifiable. Figure 5.16 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.

Thereafter, we fitted the transformed data pattern with piece-wise function, as is shown by Figure 5.17. The distribution of error between the fitted price and actual price is illustrated by Figure 5.18.

As we can see from Figure 5.17-5.18, the fitted merit-order price eliminated the stochastic movement of the price. If we simulated the price movement merely with the merit-order model, it will show a smoothed curve where the drastic jumps of price cannot be captured, which can be demonstrated by Figure 5.19.

Although it might suffice the needs of valuing a conventional generation resources, the elimination of stochastic price movement would reduce the value of arbitrage greatly as is shown by Figure 5.20.

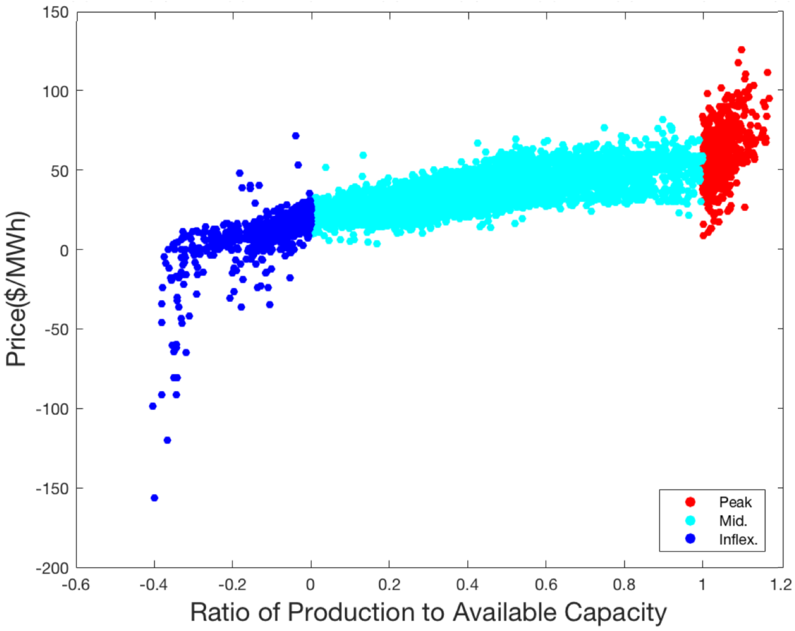

Figure 5.15: Transformed pattern of Germany day-ahead price-volume data in 2016

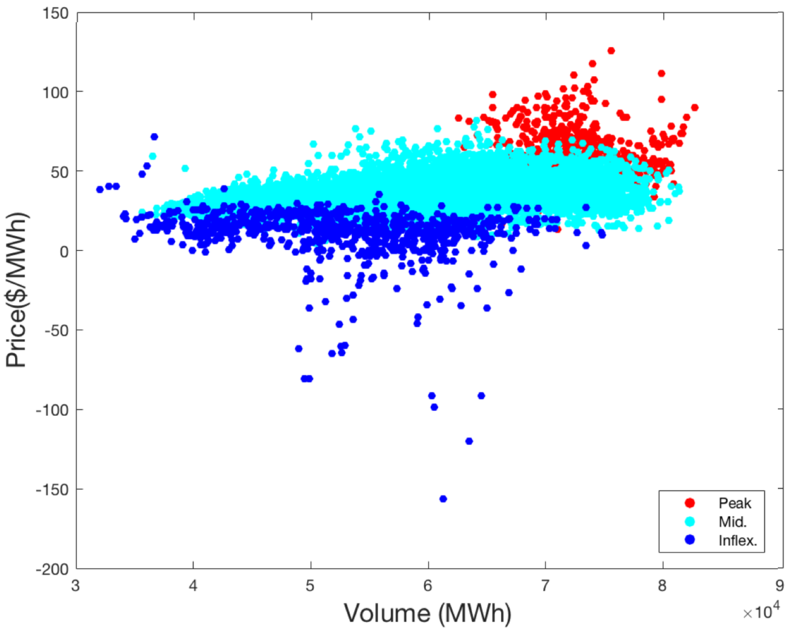

Figure 5.16: Classification of Germany day-ahead price-volume data in 2016

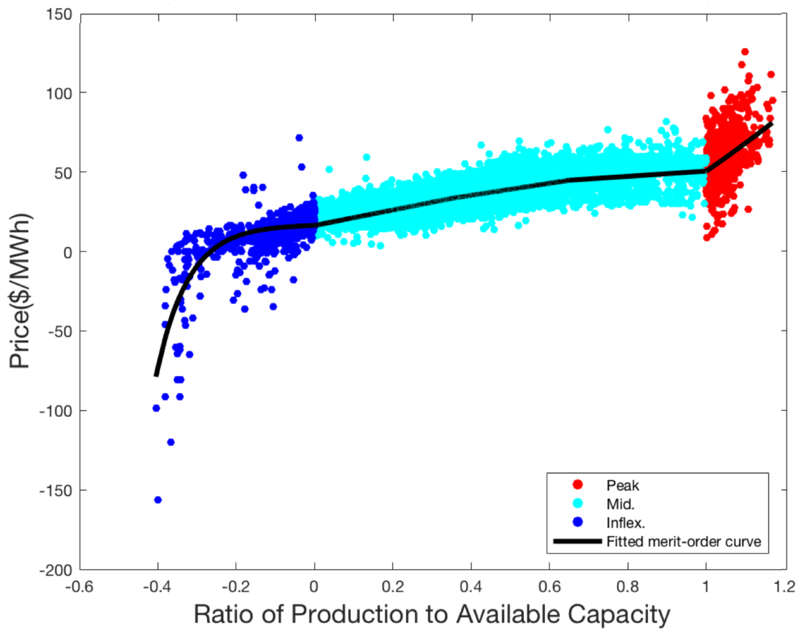

Figure 5.17: Fitted merit-order curve with Germany day-ahead price-volume data in 2016

Table 5.2: Parameters of the stochastic price movement of SARMA models

SARMA paramters	
$\phi_1 = 1.811$	$\theta_1 = -1.063$
$\phi_2 = -0.813$	$\theta_{24} = 0.692$
$\phi_{24} = 0.090$	$\theta_{168} = -0.600$
$/phi_168 = 0.692$	

Therefore, we applied the seasonal auto-regressed moving-average (SARMA) model as is described in Section 4.2.3 to simulate the stochastic components of the price. The estimated parameters of the SARMA model is listed in Table 5.3.2. Thereafter, we conducted Monte-Carlo simulations to generate a number of scenarios of 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 5.19. Using these generated price profiles, we calculated the revenue for 10 scenarios and compare the average value to the value obtained with actual price signal, which shew a perfect fitness in Figure 5.20.

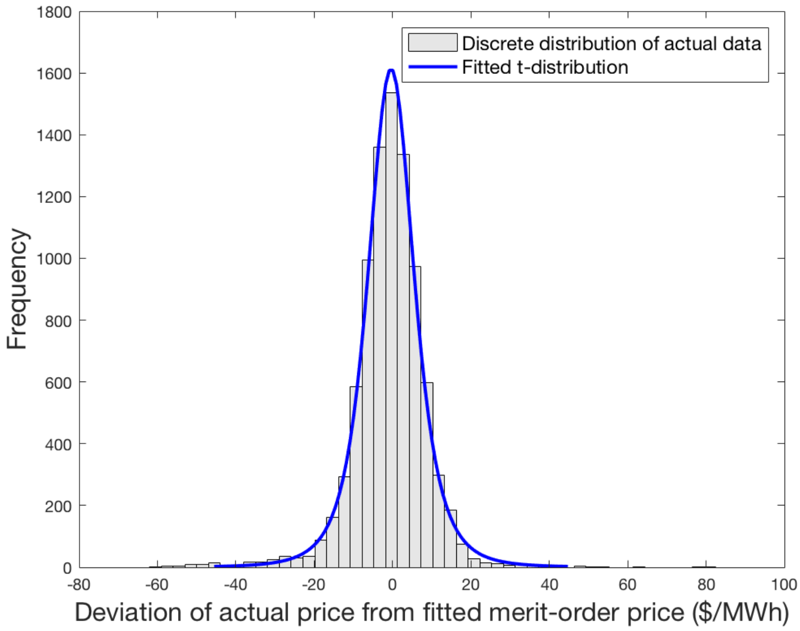

Figure 5.18: Distribution of errors between fitted merit-order price and actual price

Impact of renewable penetration

Impact of increasing flexibility on generation side

5.3.3 Impact of increasing flexibility on demand side

5.3.4 Sensitivity analysis

Limited predictibility

Responsive price

Database

Locational price

Sensitivity analysis of other parameters

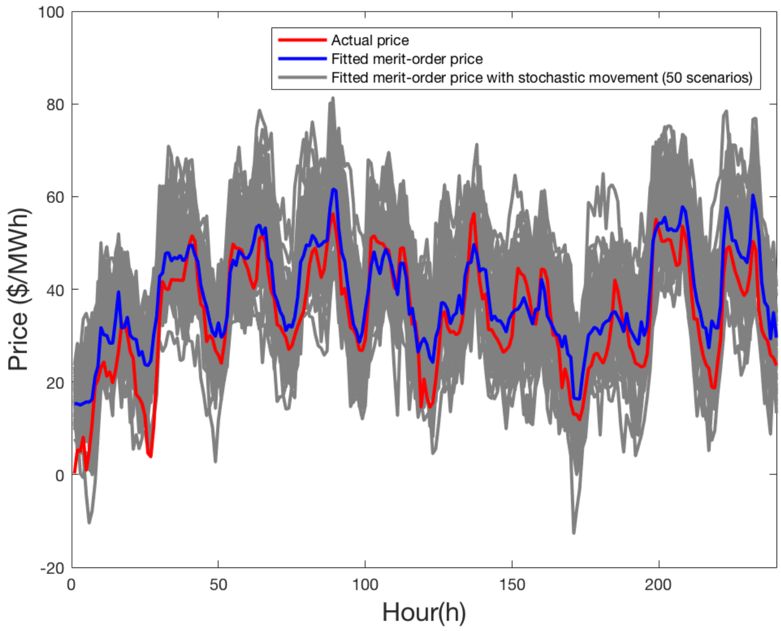

Figure 5.19: Generated price scenarios

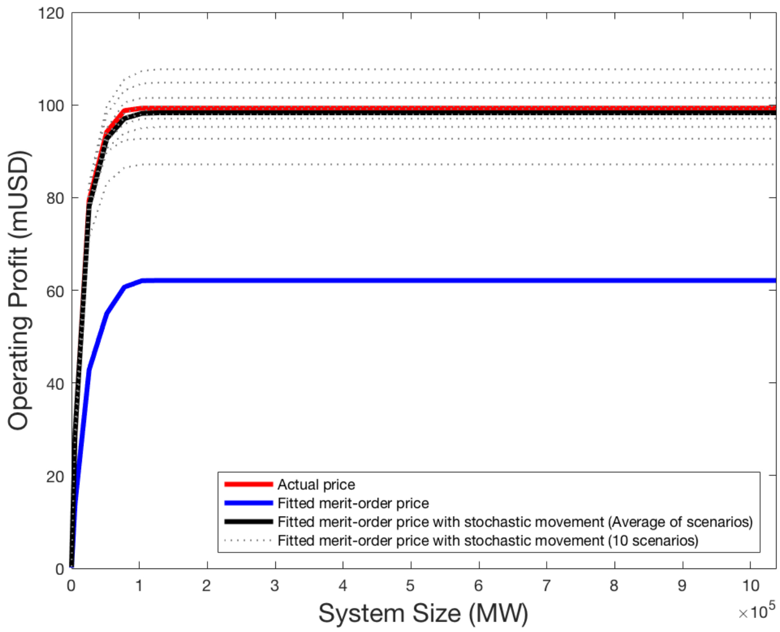

Figure 5.20: The revenue with different price scenarios

Chapter 6

Conclusions and outlook

Appendix A

Model parameters

Bibliography

[1] Frank Sensfuß, Mario Ragwitz, and Massimo Genoese. The merit-order effect: A detailed analysis of the price effect of renewable electricity generation on spot market prices in Germany. *Energy Policy*, 36(8):3076–3084, 2008.

[2] Gonzalo Sáenz de Miera, Pablo del Río González, and Ignacio Vizcaíno. Analysing the impact of renewable electricity support schemes on power prices: The case of wind electricity in Spain. *Energy Policy*, 36(9):3345–3359, 2008.

[3] Åsa Grytli Tveten, Torjus Folsland Bolkesjø, Thomas Martinsen, and Håvard Hvarnes. Solar feed-in tariffs and the merit order effect: A study of the German electricity market. *Energy Policy*, 61(June 2011):761–770, 2013.

[4] Dylan McConnell, Patrick Hearps, Dominic Eales, Mike Sandiford, Rebecca Dunn, Matthew Wright, and Lachlan Bateman. Retrospective modeling of the merit-order effect on wholesale electricity prices from distributed photovoltaic generation in the Australian National Electricity Market. *Energy Policy*, 58:17–27, 2013.

[5] Liliana Gelabert, Xavier Labandeira, and Pedro Linares. An ex-post analysis of the effect of renewables and cogeneration on Spanish electricity prices. *Energy Economics*, 33(SUPPL. 1):S59–S65, 2011.

[6] Stefano Clò, Alessandra Cataldi, and Pietro Zoppoli. The merit-order effect in the Italian power market: The impact of solar and wind generation on national wholesale electricity prices. *Energy Policy*, 77:79–88, 2015.

[7] C. K. Woo, J. Moore, B. Schneiderman, T. Ho, A. Olson, L. Alagappan, K. Chawla, N. Toyama, and J. Zarnikau. Merit-order effects of renewable energy and price divergence in California's day-ahead and real-time electricity markets. *Energy Policy*, 92:299–312, 2016.

[8] Johanna Cludius, Hauke Hermann, Felix Chr Matthes, and Verena Graichen. The merit order effect of wind and photovoltaic electricity

generation in Germany 2008-2016 estimation and distributional implications. *Energy Economics*, 44(2014):302–313, 2014.

[9] Yang He, Marcus Hildmann, Florian Herzog, and Goran Andersson. Modeling the merit order curve of the european energy exchange power market in Germany. *IEEE Transactions on Power Systems*, 28(3):3155–3164, 2013.

[10] Machiel Mulder and Bert Sctens. The impact of renewable energy on electricity prices in the Netherlands. *Renewable Energy*, 57:94–100, 2013.

[11] Manijeh Alipour, Behnam Mohammadi-Ivatloo, Mohammad Moradi-Dalvand, and Kazem Zare. Stochastic scheduling of aggregators of plug-in electric vehicles for participation in energy and ancillary service markets. *Energy*, 118:1168–1179, 2017.

[12] Xian He, Erik Delarue, William D'haeseleer, and Jean Michel Glachant. A novel business model for aggregating the values of electricity storage. *Energy Policy*, 39(3):1575–1585, 2011.

[13] Ramteen Sioshansi, Paul Denholm, Thomas Jenkin, and Jurgen Weiss. Estimating the value of electricity storage in PJM: Arbitrage and some welfare effects. *Energy Economics*, 31(2):269–277, 2009.

[14] Graeme N. Bathurst and Goran Strbac. Value of combining energy storage and wind in short-term energy and balancing markets. *Electric Power Systems Research*, 67(1):1–8, 2003.

[15] Easan Drury, Paul Denholm, and Ramteen Sioshansi. The value of compressed air energy storage in energy and reserve markets. *Energy*, 36(8):4959–4973, 2011.

[16] D. Connolly, H. Lund, B. V. Mathiesen, E. Pican, and M. Leahy. The technical and economic implications of integrating fluctuating renewable energy using energy storage. *Renewable Energy*, 43:47–60, 2012.

[17] Wartsila. Delivering flexibility in the German electricity markets: are current arrangements fit for purpose? Technical report, 2014.

[18] Christoph Möller. *Balancing energy in the German market design*. PhD thesis, Universitat Karlsruhe, 2010.

[19] Anurag K. Srivastava, Sukumar Kamalasadan, Daxa Patel, Sandhya Sankar, and Khalid S. AlOlimat. Electricity markets: an overview and comparative study. *International Journal of Energy Sector Management*, 5(2):169–200, 2011.

[20] Florian Ziel, Rick Steinert, and Sven Husmann. Efficient modeling and forecasting of electricity spot prices. *Energy Economics*, 47:98–111, 2015.

[21] Xuejiao Han, Evaggelos G Kardakos, and Gabriela Hug. Trading strategy for decentralized energy resources in sequential electricity markets : A Swiss case study. In *7th Innovation Smart Grid Technologies*. IEEE, 2017.

[22] Behnam Mohammadi-Ivatloo, Hamidreza Zareipour, Nima Amjady, and Mehdi Ehsan. Application of information-gap decision theory to risk-constrained self-scheduling of GenCos. *IEEE Transactions on Power Systems*, 28(2):1093–1102, 2013.

[23] R. Tyrrell Rockafellar and Stanislav Uryasev. Optimization of conditional value-at-risk. *Journal of Risk*, 2:21–41, 2000.

[24] D. Rastler. Electric Energy Storage Technology Options: A White Paper Primer on Applications, Costs and Benefits. Technical report, Electric Power Research Institute, 2010.

[25] Jim Eyer and Garth Corey. Energy Storage for the Electricity Grid: Benefits and Market Potential Assessment Guide: A Study for the DOE Energy Storage Systems Program. Technical Report February, Sandia National Laboratories, 2010.

[26] Philipp Grünewald. Electricity storage in future GB networks - a market failure? In *BIEE 9th Accademic Conference*, number August 2012, pages 1–23, 2012.

[27] Philipp Grünewald. *The role of electricity storage in low carbon energy systems*. PhD thesis, 2012.

[28] James Cox. How wind variability could change the shape of the British and Irish electricity markets. Technical Report September, Pöyry Energy Ltd, 2009.

[29] Agora Energiewende. Flexibility in thermal power plants with a focus on existing coal-fired power plants. Technical report, Agora Energiewende, 2017.

[30] General Electric Company. Siemens gas turbine portfolio, 2016.

[31] General Electric Company. 9HA.01/.02 GAS TURBINE, 2015.

[32] Evaggelos G. Kardakos, Christos K. Simoglou, and Anastasios G. Bakirtzis. Short-term electricity market simulation for pool-based multi-period auctions. *IEEE Transactions on Power Systems*, 28(3):2526–2535, 2013.

[33] Olivier Megel. *Storage in Power Systems : Frequency Control , Scheduling of Multiple Applications, and Computational Complexity.* PhD thesis, ETH Zurich, 2017.

[34] Björn Nykvist and Måns Nilsson. Rapidly falling costs of battery packs for electric vehicles. *Nature Climate Change*, 5(4):329–332, 2015.

[35] Anthony Barré, Benjamin Deguilhem, Sébastien Grolleau, Mathias Gérard, Frédéric Suard, and Delphine Riu. A review on lithium-ion battery ageing mechanisms and estimations for automotive applications, 2013.

[36] Kyle Bradbury, Lincoln Pratson, and Dalia Patiño-Echeverri. Economic viability of energy storage systems based on price arbitrage potential in real-time U.S. electricity markets. *Applied Energy*, 114:512–519, 2014.

[37] Dimitrios Zafirakis, Konstantinos J. Chalvatzis, Giovanni Baiocchi, and Georgios Daskalakis. The value of arbitrage for energy storage: Evidence from European electricity markets. *Applied Energy*, 184:971–986, 2016.

[38] D. Connolly, H. Lund, P. Finn, B. V. Mathiesen, and M. Leahy. Practical operation strategies for pumped hydroelectric energy storage (PHES) utilising electricity price arbitrage. *Energy Policy*, 39(7):4189–4196, 2011.

[39] Raymond H. Byrne and César A. Silva-Monroy. Estimating the Maximum Potential Revenue for Grid Connected Electricity Storage: Arbitrage and Regulation. Technical Report December, Sandia National Laboratories, 2012.

[40] Dylan McConnell, Tim Forcey, and Mike Sandiford. Estimating the value of electricity storage in an energy-only wholesale market. *Applied Energy*, 159:422–432, 2015.

[41] Asmae Berrada, Khalid Loudiyi, and Izeddine Zorkani. Valuation of energy storage in energy and regulation markets. *Energy*, 115:1109–1118, 2016.

[42] A Oudalov, D Chartouni, and C Ohler. Optimizing a Battery Energy Storage System for Primary Frequency Control. *IEEE Transactions on Power Systems*, 22(3):1259–1266, 2007.

[43] Theodor Borsche, Andreas Ulbig, Michael Koller, and Goran Andersson. Power and energy capacity requirements of storages providing frequency control reserves. In *IEEE Power and Energy Society General Meeting*, 2013.

[44] Chunlian Jin, Ning Lu, Shuai Lu, Yuri V. Makarov, and Roger A. Dougal. A coordinating algorithm for dispatching regulation services between slow and fast power regulating resources. *IEEE Transactions on Smart Grid*, 5(2):1043–1050, 2014.

[45] PJM. PJM Manual 11 : Energy & Ancillary Services Market Operations, 2017.

[46] Qi Wang, Chunyu Zhang, Yi Ding, George Xydis, Jianhui Wang, and Jacob Østergaard. Review of real-time electricity markets for integrating Distributed Energy Resources and Demand Response. *Applied Energy*, 138:695–706, 2015.

[47] PJM Interconnection. Demand Response Strategy, 2017.

[48] PJM. PJM Manual 12: Balancing Operations, 2017.

[49] Toby Brown, Samuel Newell, David Oates, and Kathleen Spees. International Review of Demand Response Mechanisms. Technical Report October, Brattle Group on behalf of the Australian Energy Market Commission, 2015.

[50] IRENA. Electricity storage and renewables: costs and market to 2030. Technical Report October, International Renewable Energy Agency, Abu Dhabi, 2017.

[51] Tesla Inc. POWERPACK Utility and Business Energy Storage.

[52] Abbas A. Akhil, Georgianne Huff, Aileen B. Currie, Benjamin C. Kaun, Dan M. Rastler, Stella Bingqing Chen, Andrew L. Cotter, Dale T. Bradshaw, and Wiliam D. Gauntlett. DOE/EPRI 2013 electricity storage handbook in collaboration with NRECA. Technical Report January, Sandia National Laboratories, Livermore, California, 2015.

[53] Tesla Inc. Home Charging Installation.

[54] Tesla Inc. Tesla Model S.

[55] National Renewable Energy Laboratory. Transportation Secure Data Center.

[56] European Commission. Passenger cars in the EU.

[57] Kraftfahrt-Bundesamtes (KBA). Monatliche Neuzulassungen.

[58] Chao Peng, Jianxiao Zou, Lian Lian, and Liying Li. An optimal dispatching strategy for V2G aggregator participating in supplementary frequency regulation considering EV driving demand and aggregator's benefits. *Applied Energy*, 190:591–599, 2017.

[59] M. Shafie-Khah, M. P. Moghaddam, M. K. Sheikh-El-Eslami, and J. P.S. Catalão. Optimised performance of a plug-in electric vehicle aggregator in energy and reserve markets. *Energy Conversion and Management*, 97:393–408, 2015.

[60] R. J. Bessa and M. A. Matos. Optimization models for an EV aggregator selling secondary reserve in the electricity market. *Electric Power Systems Research*, 106:36–50, 2014.

[61] R. J. Bessa and M. A. Matos. Global against divided optimization for the participation of an EV aggregator in the day-ahead electricity market. Part II: Numerical analysis. *Electric Power Systems Research*, 95:309–318, 2013.