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

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Chapter 1

Introduction to Flexibility Management and The Goal of This Thesis

1.1 Defining flexibility and flexibility management

Maintaining balance between supply and demand is a fundamental requirement to electric power system operations. The capability of a power system to match the supply and demand at each point of time by using controllable resources are often referred to as "operational flexibility", or simply "flexibility" [1–4]. Flexibility is therefore not a new concept. Power systems are inherently with uncertainty and variability since loads vary over time and occasionally in unexpected ways, and power plants may suffer unpredictable failures sometimes. All power systems are designed and built with certain level of flexibility to cope with those unexpected events. Conventionally, the flexibility is mainly enabled on the supply side, where dispatchable resources are controlled to adjust their outputs to match the time-varying load.

However, following radical transformation towards decarbonization, decentralization and digitalization in the energy industry, the existing operating model of electricity flexibility is being challenged and increasing interests are moving to flexibility from the load side and energy storage technologies [3, 5, 6]. These disruptions are not only technological but also institutional and managerial, and are sparking market restructures and business model innovations. For instance, new flexibility resources are typically smaller in scale compared the traditional flexible generations so the new operating model is migrating to a more decentralized approach. Flexibility management, as an emerging business term, refers to the process how those new small-to-medium scale sources of flexibility are enabled, organized and exploited to serve the needs of less predictable power systems.

1.2 Challenges in power system flexibility

The fundamental driver behind the increasing focus on power system flexibility is the global penetration of renewable energy sources (RES) such as wind and solar power [7]. Many studies show that large-scale integration of RES brings critical challenges in maintaining power system balance with existing flexibility resources [1–3, 8–14].

The impact of RES on electric power systems can be deduced from the intrinsic technological attributes of RES [11, 15]:

- RES is variable and often viewed as non-dispatchable since its output is determined by weather conditions, and furthermore

- RES is often imperfectly predicted and specific power generation is uncertain until realization.

Effects of the property being non-dispatchable can be illustrated by introducing the concept of "net load", also referred to as "residual load", which equals the total system load minus the renewable generation and thus represents the load that needs to be served by non-RES resources [1, 9, 16].

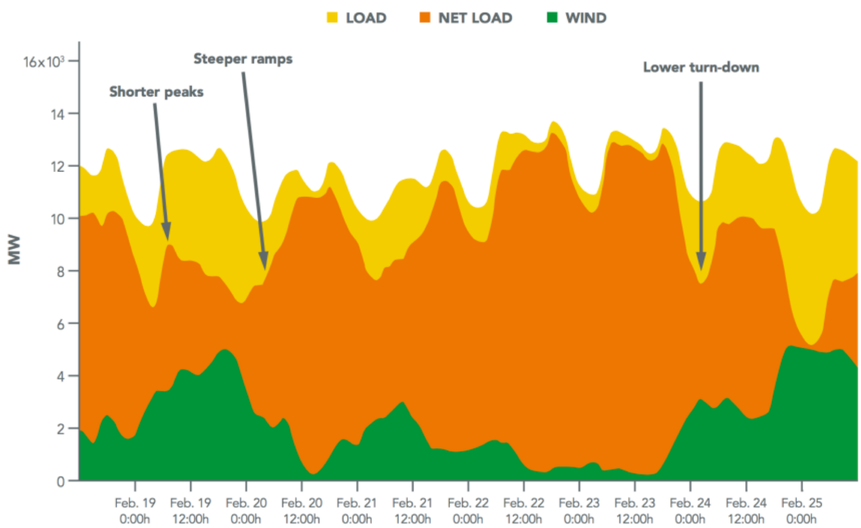

Figure 1.1: An illustrative example of net load profile [1]

Figure 1.1 shows an example profile of net load, based on which we can see how RES is changing the profile of the existing non-RES generation:

- **Shorter peaks**: resulting in fewer operating hours for conventional peak generators, affecting their cost recovery and consequently their ability to attract investors and maintain security security of supply

- **Lower turn-down**: diminishing the base load which should be stable at a higher level without RES, creating challenges to base generators who have limited operational flexibility to vary their outputs, and

- **Steeper ramps**: demanding higher performance in delivering flexibility, eliminating relatively low-grade resources from serving the needs for flexibility.

It can be seen that the whole span of the current generation portfolio serving base, flexible and peak power is under great pressure as a result of the RES growth.

The issue of the forecast error, on the other hand, requires the dispatch of flexibility close to real-time operation. This is an explicit issue in places where those activities are organized through power markets. In present power markets, the major part of the scheduling and pre-dispatching is determined ahead of the operating day based on forecasts and errors deviated in real time from the schedule are mostly depending on imbalance settlements via so-call frequency control ancillary services which are typically more costly [17, 18]. The intra-day market with higher resolution of price signals and shorter prediction horizon toward actual operation is a feasible solution and implemented in many markets [18] but intra-day markets are empirically prone to low liquidity in may regions [3, 19, 20]. Without structural improvements in the market design, the demands for frequency control services would increase significantly and thus add burdens to the power system operators [21–23] as well as raise electricity prices for the end users. Measures such as improving day-ahead forecast [24], developing short-term frequency control products [25], and optimized intra-day [20] and balancing market frameworks [26], have been proposed. Being sensitively depending on the market arrangements, existing businesses may be disrupted significantly by any of those market restructures.

Besides, solar power which is forecasted to have even higher potential than wind power in the long run is tending to grow in distributed patterns [7, 27, 28]. With the conventional centralized deployment of flexibility, local congestion is likely to worsen [3, 29] which drives the needs for extensions of transmission and distribution capacity.

Collectively, RES penetration urges innovations in both technology and market design. Failing to do so would burden power system operators with higher expenses, potentially reducing the revenue scream of existing market players and/ or leading to significant curtailment of RES.

In addition to RES, the electrification of transportation, i.e. the penetration of plug-in electric vehicles (EV), is emerging more recently to be a second game changer. Facilitated by support policies from states and cities to uncap their multiple benefits such as transport decarbonization, air pollution reduction, and energy efficiency and security, the growth of EV has been accelerating significantly, having exceeded the global threshold of cumulatively 2 million in 2016 [30]. Although a promising source of flexibility is the emergence of vehicle to grid (V2G) technologies [31–33], barriers to its success are not trivial. The growth of EV may outpace developments in flexibility resulting in negative impacts such as increasing peak demand and potential local congestion [34, 35].

It has been pointed out that the lack of flexibility can be identified more intuitively by signals such as [1, 2]:

- difficulty balancing demand and supply, resulting in frequency excursions or shedded load,
- significant renewable energy curtailments,
- negative market prices, and
- high price volatility in wholesale power markets.

Although having been discussed extensively for years in academia and by industry experts, it was not until quite recently when signs of inflexibility had been witnessed did the public start to be indeed aware of the challenges on power system flexibility. For instance, negative pricing in wholesale power spot market was first introduced in 2007 in Germany intraday market and in 2008 in Germany/Austria day-ahead market [36], but real attention from the public came after 146 hours over 24 days were observed in the day-ahead market in 2017. Another famous example could be the power outage in South Australia that happened on September 28th 2016. After a widespread debate, Australia Energy Market Operator (AEMO) finally concluded in its investigation report that the generation deficit of wind farms due to unexpected operation of a control setting responding to multiple disturbances, led to the power blackout [37]. This aroused public worries on supply security deriving from RES generation. As one of the follow-up actions, AEMO partnering with Tesla Inc., one of the leaders in global battery and electric vehicle markets, built the worlds' largest battery energy storage system (BESS) in South Australia [38].

These developments imply a proper timing for technology vendors to update their assessment on the market, as interests in flexibility management from the public and thus their potential customers have significantly increased.

1.3 Technology options for system flexibility provision

Thanks to significant developments in energy storage technologies and information communication technologies (ICT) in recent years, the landscape of flexibility solutions has changed vastly. While it was in the past limited to centralized solutions, extracting flexibility from distributed resources and operating in an aggregate way has gradually become both technically feasible and economical viable [1–3, 9]. A systematic summary for these various possibilities can be found as Figure 1.2.

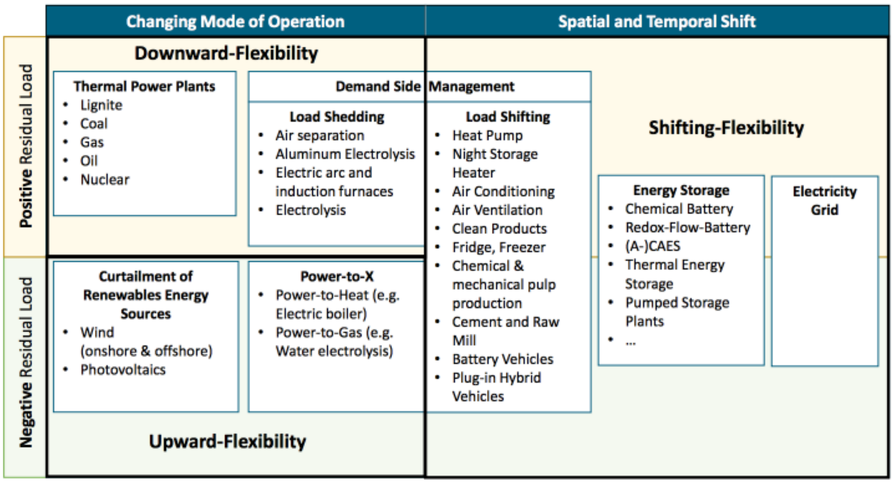

Figure 1.2: Catalog of flexibility solutions [9]

Technologies for flexibility are categorized by their type of provision:

- **Downward-flexibility**: shedding demand or uplifting supply to reduce the positive residual load,

- **Upward-flexibility**: dropping surplus RES feed-in or increasing demand to mitigate negative residual load,

- **Shifting-flexibility**: shuffling surplus energy from regions (or time steps) with negative or lower residual load to other regions (or time steps) with higher residual load.

It can be clearly seen that the term demand-side management (DSM), or often referred to as demand response (DR), is actually an umbrella term for a suite of different technologies with disparate flexibility mechanisms.

Combining the evaluations carried out by several studies [1–3, 9, 39], the characteristics of different technologies can be summarized on a high level as:

- **Generation**: i.e. flexibility provision by varying power plant outputs.

  This is by far the most mature technology and typically not constrained by the duration of flexibility provision nor how often to be activated. Activation time and ramp rate are the main issues for flexibility from power plants, especially conventional power plants using stream turbines, e.g. coal, lignite and nuclear power plants. Although output adjustments can be done within 1 hour, a cold start may take up to 100 hours or at least 4 hours even with the state-of-the-art thermal power plants [9,40]. Gas turbines are more flexible even compared to some other advanced technologies that are to be introduced later, so they are viable as a decent option to increase system flexibility [9].

Cost is a complex topic and varies greatly between different type of generation technologies but in general flexible supply assets are still lower than most emerging flexibility technologies. However, building power plants is not an economical option to cover the extreme events that are rarely seen, as heavy fixed costs of building power plants are unlikely to be recovered in this scenario. Meanwhile, noxious emissions related to consumption of fossil fuels raise the uncertainty of operational viability in long term.

- **Load shedding**: i.e. load curtailment, mainly enabled by disrupting some energy-intensive industrial processes. In contrast to load shifting, shedded load will not be compensated later on as most of the time the industrial processes are running at their maximum allowances.

  Load shedding applications can provide fast responses, but are constrained at duration and numbers of activation. Nonetheless, short timespan of flexibility provision and limited occurrence fit the characteristics of extreme disturbances in power systems, so load shedding can be deployed for that specific purpose.

  The activation cost is essentially the loss caused by the disrupted productions so is indeed an adverse factor. The fixed cost, on the other hand, is less concerning as most industry plants nowadays are already equipped with automatic and intelligent energy management systems.

- **RES curtailment**: i.e. regulating the outputs of RES plants downwards.

  Technically, there are few constraints for RES curtailment as they can be performed promptly and frequently, and last for an indefinite time period. However, since curtailments will waive the revenues that would otherwise be received by selling electricity in the market, RES operators are discouraged to do so. Although a list of measures are possible for power system operators to mandate curtailments, it is contradictory to the overarching mandate of decarbonization.

  Therefore, we deem the RES curtailment as a compromise and the last option if the needs for flexibility cannot be fulfilled by any other means.

- **Power-to-X(P2X)**: i.e. consuming excess electricity to produce other energy carriers, e.g. hydrogen, methane, heat, or other less conventional outputs.

  P2X technologies can also provide fast response and theoretically last for an indefinite period of time. However, in reality it is constrained by how the by-products are stored and utilized, and values of the by-products also vary significantly in different situations. For instance, while heat generation is valuable in winter, it is likely to be counter-productive in summer.

  Regarding the cost, power-to-gas technologies require significant high initial investments on equipment while power-to-heat costs much less with the core components being boilers and heat tanks. Overall, the economics of P2X is still a challenging issue as the value can be harvested only if the by-products are competitive compared to goods by other production methods. However, production of P2X is destined to be intermittent as it would only be activated while upward-flexibility is needed reducing economic viability.

- **Energy storage**: a system that can absorb surplus energy in time with negative or low residual while release energy in time with higher demand. Due to its technical nature, the energy storage can act on both supply and demand side or be viewed as a third pillar of flexibility in conjunction with supply and demand [41].

  Energy storage itself is an umbrella for an abundance of technologies, including battery energy storage systems (BESS), pumped hydroelectric storage (PHES), compressed air energy storage (CAES), flywheel, thermal storage, and others. These technologies vary significantly in their mechanism and thus in technical parameters such as size and efficiency as well as in performances, e.g. duration, action time, cost, etc. Among them, BESS could be the most attractive with fast response (activated within seconds), decent duration (up to 10 hours) and most importantly few external dependencies such as geographic topology. Cost is the main concern for batteries, but is decreasing dramatically in recent years [42]; see Figure 1.3.

- **Load shifting**: corresponding to the concept of demand response in a narrower sense where responsive loads are enabled by direct control signals or indirect price signals.

  There are a great variety of load types that can be exploited for load shifting, so similar to energy storage, load shifting contains a list of subcategories. However, unlike other technologies that can be characterized by standard models, load shifting shows a higher diversity. This is because the characteristics of a load shifting system would be

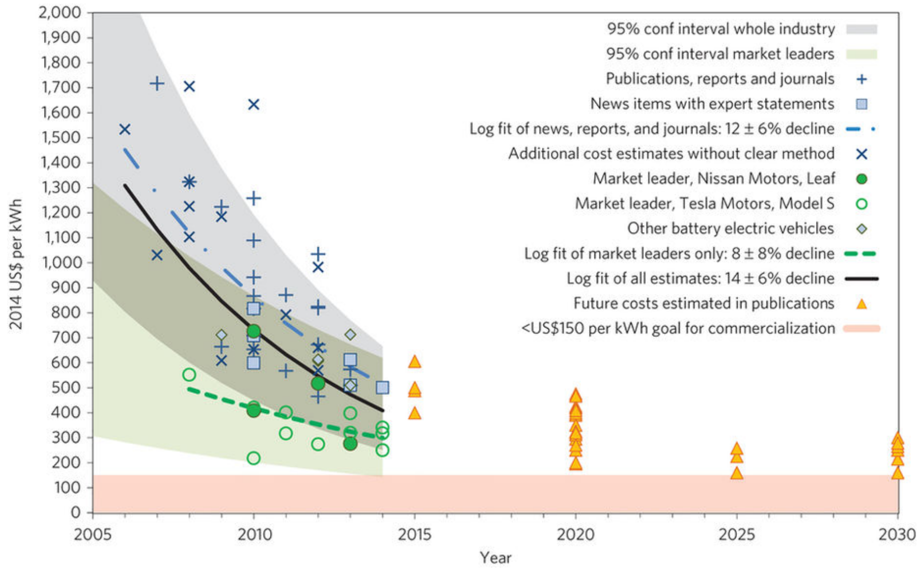

Figure 1.3: Cost of Li-ion batteries for electric vehicles [42].

sensitively affected not only the technical parameters of load but also the control strategy and the users' preferences. Nonetheless, the load shifting in general has short activation time (within seconds to minutes), short duration (typically 0.5 to 8 hours) and relatively low cost (even close to zero if appliances come equipped with control devices).

- **Electricity grid**: i.e. extension of distribution and transmission capacity. Distinguishing other technologies discussed above that shuffle electricity temporarily, the grid extension is the only option that deals with fluctuations of residual load spatially.

  Flexibility from the transmission and distribution (T&D) network has the fastest response and indefinite duration so together with generation flexibility it has been a main solution for conventional power system flexibility. However, challenges come from the development of distributed energy resources (DER) which disrupt the existing T&D systems with altered electricity flow profiles. Congestion in the network is a major bottleneck for delivering flexible power in the grid. Further grid infrastructure upgrade may be necessary but leads to high expenses so may anyway need to be complemented by other technologies introduced above [1].

Studies reveal that an abundance of different flexible technologies will be available in the future, and it is well agreed that no single option would be sufficient to individually provide flexibility to power systems [1–3, 9]. Determining the best mix of options needs to be carried out on a case base and requires significant efforts as being a complex techno-economic and policy issue.

The innovations in technology, changes in market frameworks and cost reductions will collectively change the landscape, and overall create more available solutions for players. Therefore, technology vendors are closely watching the development of technologies and constantly updating their view on which technologies to supply.

1.4 Applications, benefits and business models

With the dual trends of both increasing level of RES penetration and growing opportunities from technological development, the necessity of increasing power system flexibility provision is being realized by policymakers, market designers, companies and the public. On the policy level, we have witnessed established rules that were based on the conventional technologies being constantly revisited and improved to better embrace new technologies. A good example is in the United States where the Federal Energy Regulatory Commission (FERC) has issued orders seeking the removal barriers and discrimination for emerging flexibility technology in markets organized by independent system operators (ISO) and regional transmission operators (RTO). Examples include Order No. 784 [43] published in 2013 calling for third-party flexibility provision in the ancillary service markets and Order No. 841 [44] published in 2018 opening gates for energy storage in wholesale energy markets. Similar efforts have been witnessed in Australia [45, 46], South Korea and Japan [47]. European markets may lag behind in terms of implementation but active discussion and review on existing policies are being carried out [48–50]. Inspired by incentives from policies, innovative business models are being tested, for example the rise of aggregators and virtual power plants (VPP), a special case of aggregation with distributed generation being the core.

Facing such a disruptive environment, it is a crucial task for technology vendors to update their understanding on the needs and use-cases of their utility customers in order to strategically plan their business and make decisions. The ask is understanding the applications and benefits of flexibility management. Here "application" refers to a use where flexibility is exploited for a certain aim via certain procedures, and "benefit" denotes a value that can be evaluated in monetary or financial terms. Thereby the combination of players, applications, benefits and solutions constitute to a concrete business model.

More activities are observed in economies with liberalized power markets. This is not only because business innovations are inspired by competition in those markets and new entrants are allowed to bring more disruption, but also because of the fact that most of the major economies today have implemented or been in the process of power market liberalization [17, 51].

A schematic illustration of liberalized power markets can be found as Figure 1.4[1].

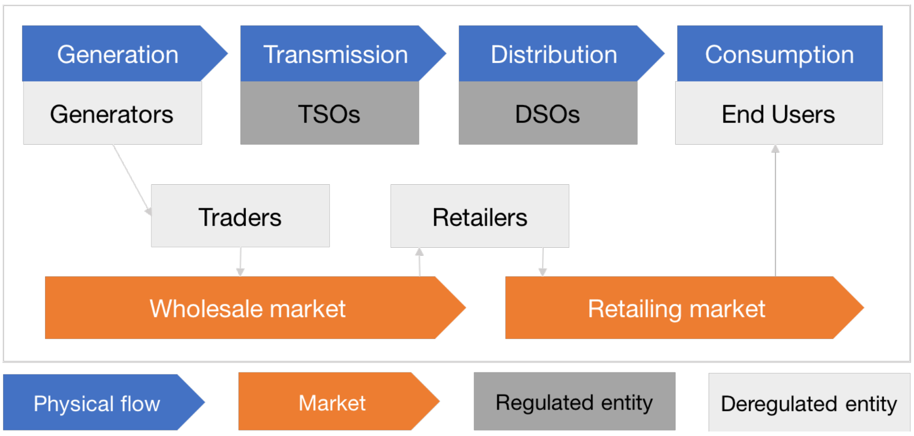

Figure 1.4: Schematic illustration of the liberalized power market

Besides the conventional players shown in the chart, it is worthwhile to pay more attentions on the new role of aggregator. Aggregators are new entities in the electricity market that act as mediators / brokers for end-users to participate in wholesale markets [47, 52–55]. Unlike conventional retailers who are just responsible for one-way electricity sales to the consumers, aggregators enable two-way interaction with the end-users that make it possible for distributed energy resources (DERs) to be managed and utilized for a broader range of wholesale services.

Varying from case to case, the wholesale electricity market is typically a bundle of different markets with distinct functions and possibly organized by various market operators. These functional markets include:

- **Spot market**: also referred to as electricity market in a narrower sense, is the market where electricity is traded for immediate delivery. Typically, the spot electricity market is organized day-ahead but sometimes an intra-day or real-time market exists in some economies.

- **Financial derivatives market**: is a complement to the spot market. Electricity spot markets are typically highly volatile due to the physical nature of power systems. Financial derivatives, e.g. forwards, futures, swaps and options, are necessary tools in order to hedge the risk of trading in electricity market. They could be offered as standard exchange traded products in organized markets or via bilateral over-the-counter (OTC) contracts.

[1] In the figure, TSO is abbreviated for transmission system operator and DSO is for distribution system operator

- **Ancillary service market**: is the market to supply services for the power system operators in order to maintain key technical characteristics of the system, including standards for frequency, voltage, network loading, and system restart processes.

- **Capacity market**: is a mechanism to pay capacity resources to be available to provide energy in order to ensure adequacy of electricity supply. The capacity is not always remunerated explicitly in some markets and those markets are therefore referred to as "energy-only" markets [45].

Applications of flexibility management exist in all of these markets. Besides the financial derivative that is beyond the scope of focusing from a technology vendor's point of view, the major applications of flexibility the other markets are summarized as following:

- **Electricity time-shift in wholesale spot market**: for shifting-flexibility technologies defined in the preceding section, they are able to shuffle electricity temporally so that can purchase inexpensive electricity that is available during periods when price is low and sell in high-pricing hours. The buying and selling activities can de done by real transactions in the wholesale market, or alternatively they can be realized by offsetting the players' position in the wholesale market. For instance, a player with a short position in the market may turn to flexibility resources for electricity output to offset the needs for purchasing and in this way the electricity can be conceived as sold by the flexibility resource while it does not necessarily involve a real transaction via wholesale market. It shall be noted that the electricity time-shifting in wholesale energy market is commonly referred to as "**arbitrage**" by researchers on power system flexibility [56–64] and inherited by this thesis, but the term "arbitrage" does not strictly fit in its finance-centric definition[2]

- **Electricity time-shift in retail market**: similar application of electricity time-shift can be realized in the retail market while the end-consumers are charged based on time-of-use tariffs. Conventionally, end-consumers do not have the capability of electricity generation and thus are not considered to inject electricity to the grid so the extraction of energy from flexibility resources is merely able to offset the users' needs. However, situations have altered with the penetration of distributed generations, mainly distributed RES, making the situation

[2]In finance, arbitrage is defined as the simultaneous purchase and sale of identical or equivalent commodities or other instruments across two of more markets in order to benefit from a discrepancy in their price relationship, while arbitrage using flexibility does not always occur at the same time and is typically perform in only one market [65].

more close to the cases in wholesale markets. Nonetheless, the ability of consumers to benefit from this on an individual level is usually quite limited, which is why aggregators have moved in to make a liquid market.

- **Frequency control in ancillary services market**: frequency deviation is the most essential and immediate result of mismatching between supply and demand in power system. Recalling its definition, flexibility is without doubt most suited for providing frequency control services by quickly restore the divergences between generation and consumption.

- **Supply capacity in capacity market**: as is introduced earlier, the capacity market is set up in some power markets to ensure supply adequacy. Flexibility that is able to shift the supply or shed the load can increase the resources adequacy on generation as well. Some capacity markets have admitted emerging flexibility technologies to receive remunerations, which is virtually a strong incentives to incorporate more flexibility in a power system.

- **Transmission congestion relief**: the transmission capacity has to keep pace with the peak demand. However, being disrupted by RES integration and EV penetration as we have discussed previously, the transmission system operators (TSOs) are under great pressure to upgrade infrastructure which is costly. Distributed flexibility enabled by emerging technologies, can be deployed at locations that are prone to variances in demand. By smoothing demand profiles and thus shaving the peaks in those areas, TSOs are relieved of congestion with lower transmission capacity and therefore cut expenses on transmission infrastructure.

Besides what is listed above, there are other applications that can be realized by certain type of flexibility technologies. For example, battery energy storage systems are normally able to provide voltage support and black start services [65–67]. However, these applications do not come from the ability of adjust supply and demand as we defined flexibility, so are excluded here.

Further to these applications, we need to understand the benefits that can be captured by users of flexibility. In this way, the benefit represents the willingness-to-pay (WTP) of the potential of of technology buyers, so can be an indicator to estimate the market potential for technology vendors. There two types of benefit:

- **Variable income from power markets**: is the change in monetary receivables from power markets for players, which can be increased revenue or avoided losses that result from utilizing flexibility. This corresponds to deregulated players who are capable of participating in markets where flexibility has value as introduced earlier. These benefits can be calculated directly with power market data.

- **Deferred infrastructure expense**: match cases where players have certain obligations to fulfill. Emerging flexibility technologies can provide them solutions with reduced cost. This typically corresponds to the situation of regulated entities who are mandated to offer services with lowest possible cost. Their activities in power markets are sensitively controlled. The calculation for these benefits is less straightforward and requires comparison between proposed flexibility solutions to infrastructure investment. In non-liberalized markets benefits of vertically-integrated utilities can be categorized here.

Recalling the applications discussed earlier, apart from the transmission congestion relief where the benefits can be deemed as deferred expenses of TSOs, benefits of the other application can be all realized via power markets.

The potential business cases can be summarized on a high level as Table 1.1.

Table 1.1: Summary of potential business models for flexibility management

Application	Market	Benefit	Player	Solution
Electricity time-shift	Wholesale spot market	Variable income	Generator, trader, retailer, aggregator	Temporal shifting-flexibility
Electricity time-shift	Retail market	Variable income[a]	Consumer	Temporal shifting-flexibility
Frequency control	Ancillary service market	Variable income[b]	Generator, retailer, aggregator	All options
Frequency control	Ancillary service market	Deferred expenses	TSO, DSO	All options
Supply capacity	Capacity market	Variable income	Generator, aggregator	Upward- and shifting-flexibility
Transmission congestion relief	-	Deferred expense	TSO, DSO	All options

[a] Here refers to reduced energy bills.

[b] Both increased revenue by providing frequency control service and avoided losses due to obligated charges are possible depending on market specifications.

Finally, recalling our definition of flexibility management that is the process how those emerging flexibility solutions are enabled, organized and exploited to serve the needs of power systems, the role of technology vendors are clear in each of the cases listed above, which is:

- Enabling flexibility - selling infrastructure (hardware) and technologies (software), and
- Organizing flexibility and exploiting the benefits - providing consulting or managed services.

Certainly, depending on different market regimes and specific conditions, the business model and associated values could vary significantly, which is the essential rationale of carrying our this study.

1.5 Research questions and scope

Based on the observations introduced above, we perceive a promising business area. However, more concrete analysis both qualitatively and quantitatively would be necessary to support strategic decision making on flexibility management. Therefore, this thesis is designed to provide references for strategic decision making by answering the following questions:

- What is the market value of flexibility
  - in different markets?
  - using different technologies?
- How will this value change in scenarios with
  - technological development - reduced costs?
  - increased renewable penetration?
  - other key factors?

In order to answer these questions, we first map the landscape of flexibility management comprehensively and then conduct case-specific valuations of markets for flexibility management. A techno-economic model is established for the sake of quantitative analysis. It shall be noted that although some forward-looking analysis is included, the main purpose of this study is to offer a clear understanding of current situations and a framework that can be reused in the future to update this view.

Since flexibility management broadly covers a wide area of the technologies and economics of power systems, it is necessary to narrow the scope of this study to the selected topics.

Scope of applications and benefits

First of all, we focus only on deregulated players in liberalized power markets who can faster realize the benefits of technological disruption and innovation. The business cases related to regulated entities such as TSOs and DSOs are out of scope.

Secondly, this thesis focuses on applications in wholesale markets rather than retail markets as the end-consumers are not the primary customers for flexibility solutions. With respect to exploit action of distributed energy resources at the end-users' sites, we would only conceive the business cases involved with aggregators whose value realizations are also mainly in the wholesale markets.

Thereafter, what remains in our scope is: arbitrage in wholesale spot markets, providing frequency control in ancillary service markets and supply capacity in capacity markets. However, since capacity markets are not pervasive common practice in all regions, we will not include them in the core focus.

Finally, associated with the scoped applications, benefits are mainly variable incomes from power markets. In order to make it more clear, we further restrict the benefit being explicit monetary receivables from power markets, while all other associated benefits or by-products such as the societal goodness are excluded from consideration.

Scope of technology

This thesis is focused on small-to-medium scale emerging flexibility solutions in low-to-medium voltage level, so flexibility provisions from conventional generation and pumped hydro energy storage (PHES) are excluded. Electricity grid extension also falls into this category, plus it is mainly of interests for TSOs who we have already excluded from our scope of applications.

Secondly, RES curtailment as is mentioned previously is considered as a compromise rather than opportunity. The benefits of RES curtailment may be valued from a system point view for grid stability maintenance. It will usually lead to no increase on explicit revenue for the players in power markets that is of our interests, unless the RES operators are obliged to meet the schedule and are punished for deviations.

P2X technologies are also excluded, because the values of its by-products such as hydrogen and heat are hard to account in a generic way and definitely not an explicit revenue from the power markets. Load shedding is out of scope for similar reasons, plus it is not an emerging technology with few growing opportunities for technology vendors.

Hence, we keep energy storage (excluding PHES) and demand response (load shifting) in our scope. It shall be noticed for qualitative analysis, it is normally not necessary to break them further up to sub-categories. e.g.

thermal storage versus chemical storage, DR with air conditioning versus DR with heat pump , as the overall dynamics in terms of flexibility provision are generally unified. Furthermore, it is observed that in terms of policies and market rules they are seldom distinguished by technological sub-types [43, 44, 68]. However, when quantitative analysis is to be performed where technical performance and cost dynamics are to be studied, further distinction is unavoidable. In those cases, we have selected battery energy storage systems (BESSs) and electric vehicle to grid (EV2G) as two representatives of energy storage and load shifting respectively.

Scope of geographies

Finally, for case studies, we scoped out three geographies with distinct power market regimes, i.e. PJM Interconnection in the United State, Germany, and New South Wales in Australia. The rationale is to select one geographic market from each of Americas, Europe and Asia-Pacific respectively.

Outline of the thesis

The remainder of this thesis is structured as follows:

- **Chapter 2** reviews the existing research works related to flexibility management, with a special focus on the quantitative valuation methodologies.
- **Chapter 3** maps the landscape of flexibility management by studying the market frameworks and the role of flexibility management in a generic way. Deeper analysis on value creations of flexibility management in different use-cases would be presented.
- **Chapter 4** introduces the methodology how the techno-economic model is established to make quantitative estimations.
- **Chapter 5** presents the results in three cases, i.e. PJM Interconnection, Germany and New South Wales. The case-specific business cases together with their quantified market potential and profitability would be provided, based on which we made analysis and recommendations for technology vendors.
- **Chapter 6** summarizes the main findings and conclusions. Outlook and recommended improvements by future works are also provided.

Chapter 2

Sizing and Valuation of Market for Flexibility Management: A Literature Review

This chapter reviews the existing research works with a special focus on methodologies that are related to quantifying the market for flexibility management. It was found that our research questions are not perfectly answered by the academic articles since they have different stakeholders and perspectives. However, researchers have developed a number of validated methodologies which are of great reference value for this study. We mapped the studies with different approaches and selected the proper ones considering both effectiveness and computational tractability of the methods.

2.1 Stakeholders and their perspectives

In this thesis, we aim at providing market analysis and valuations to support strategic decision making of technology vendors. There are similar works conducted by other firms and consultancies but their analysis along with the models are rarely made public [69], because of concerns on commercial confidentiality. As a consequence, we referred to literature published either in academic journals or by regulated entities such as TSOs. Their motivations are normally disparate from ours in many ways since they were targeting at different audiences. We categorize those works into two groups with distinct perspectives.

Micro-perspective

The first category refers to works that are concerned with the techno-economic performance of specific technologies in a given system/ market context as well as the value to one or few individual firms. This perspective is taken mainly to serve technical experts, flexibility project developers or investors.

In these works, valuation is usually a necessary component. The majority of these studies are made to propose novel technologies, control algorithms and bidding strategies etc.. Valuation in these works is a metric to assess the technological feasibility and economic profitability in order to prove their concept. Beside, there are reports that exclusively focus on the valuation in order to provide references on specific technologies or real projects [56, 57, 59, 62, 64, 70].

Generally, this perspective shares the same interest as ours that is to maximize the financial benefits of market players. However, researchers tend to focus on a certain specific point and put extensive efforts on it. The associated complexity does not always add additional value to our purpose of assessing the total value of a market. Instead, due to limitations on computational tractability, it is challenging and time-consuming to apply these methodologies for dealing with large-scale data-sets. Most of their results are proof-of-concept for their methodology so cannot be used as direct inputs for our analysis. Besides, their models have many implicit dependencies on market conditions so are less flexible while directly port into studies for a different market. Finally, most of these studies would assume their system size small enough while some market constraints such as liquidity are ignored.

Macro-perspective

Another perspective is taken by publications made for the interests of policymakers, market designers and grid planners. These studies standing on a macro-perspective and would investigate the benefits or requirements for flexibility for power systems. They primarily pursue to achieve lowest system cost to ensure the adequate provision of flexibility. It is worthwhile to mention that these exercises done by grid planners, power system operators, and micro-grid operators are virtually investigations on deferred infrastructure expenses [41, 71, 72], which are however not within the core scope of this study.

Disparate in objective, the results derived based on their models would be of less reference value for us, since we are primarily focusing on what can be retrieved by free players in power markets. Although their outputs are often on a whole system level which look closer to estimations for the total market potential than results of studies with the micro-perspective, it shall be noted that it is not always symmetric between remunerations obtained by players and contributions they make to the system due to imperfect market designs. For instance, in a paper that conducted valuations from both micro-perspective and macro-perspective, it was found that in several ISO markets in the US the revenue obtained by flexibility suppliers was substantially less than the net benefit contributed to the system [73].

Therefore, quantitative models developed in these reports will be seldom referred by our study. Nonetheless, analysis and conclusions in these studies could help us better understand the needs of those policymakers, market designers and grid planners, which would have significant impacts on the landscape of flexibility management, so will be incorporated in our qualitative assessments.

It is worthwhile to emphasize that both perspectives have their own limitations. The models with micro-perspective are generally more precise but often case specific without a global view, while models with macro-perspective are very inclusive but unable to adequately represent all constraints and needs of each entities [69]. However, for each group of stakeholders, it is virtually helpful to understand the rationales of the other group as well. Knowing the views of policymakers, market designers and grid planners will help players in power markets foresee the future movement of regulatory and market conditions so that make better decisions. On the other hand, policymakers shall consider the needs of market participates so that can better encourage their participation by well-designed incentives.

As a consequence, there are researchers who would conduct studies either with both perspectives in one piece of work such as [57, 74] or internalizing some decision factors from the other perspective into their own models, making the boundary less clearly demarcated. Nevertheless, in general we would base our methodology primarily on works with micro-perspective due to the match of interests.

2.2 Methodologies for quantifying the value of flexibility

Since our study is focused on income of flexibility management from power markets, it is necessary to incorporate power market modeling techniques. These models are found to be typically built in an optimization framework [69, 75, 76]. An optimization is applied to select the best combination of decision variables that maximizes the value of an objective function from some set of available alternatives, subject to some set of technical and economic constraints. In studies of our interests, the combination of decision variables is typically the dispatching plan of flexibility resources, and the objective function calculates the revenues or profits to resource owners, and thereby the optimization is to estimate the maximum possible value obtained by players with defined strategy and subject to constraints from markets and technologies.

In terms of detailed implementation, these models can be classified into many different approaches. Beyond briefly introducing these approaches, we would analyze the rationale and proper use-case for each approach and then decide which ones to follow.

2.2.1 Regarding market power: price taker versus price maker

In economics, market power refers to the capability of a market participate to manipulate the price of an item to raise its own financial or strategic benefits. Market players with market power are often referred to as "price makers" while those without market power are called "price takers". It is worthwhile to mention that in perfectly competitive markets, market participants have no market power [77].

In the business of flexibility management, players may be able to gain market power by deploying flexibility [69, 78, 79]. This topic has attracted extensive attentions from researchers and many methodologies have been developed based on multi-optimization equilibrium modeling or making price as a function of decisions. However, due to computational complexity, these methodologies are seldom used for valuation of real markets but more often for other use-cases, which are to be introduced in the reminder of this section.

Single-optimization modeling vs. multi-optimization equilibrium modeling

Single-optimization modeling is formulated with only one objective function, which represents the behavior of one entity without considering the interactions with other actors. Single-optimization modeling is relatively easy to be formulated and solved with some established and powerful toolkit. Therefore, this modeling technique is adopted by most of studies on quantifying flexibility value, especially for those which were carried out based on real-world market data with a long span of time [56, 57, 59–62, 64]

Multi-optimization equilibrium modeling considers the simultaneous benefit maximization of several entities to simulate the competition behaviors between them. Besides the lower level problem where each entity has their own strategy and objective, there is a upper level problem where the market clearing is simulated with interaction between entities under consideration. The upper level simulation usually requires advanced modeling techniques, e.g. agent-based modeling [80–82] and game theoretic approaches [53, 78, 83, 84]. The computational complexity will rise including the introduction of non-linearity, which will be discussed later in Section

2.2.4, and thus shall be only used for necessary cases.

The main use of multi-optimization equilibrium modeling is to understand the market power and price maker effects. This could help market participates who have certain level of market power to strategically gain advantages in competition. For instance, Schill *et al.* [78] studied a case in Germany how the strategy on energy storage operation of major players as price makers would influence their own and other price takers' profits. Similar works have been performed for distributed generation (DG) aggregators [85], DR aggregators [55] and more specialized EV aggregators [86]. Market designers may also need it to understand the impacts of participation of new flexibility players and thus better organize their markets by eliminating possible market power [87–89], or alternatively concentrating market power to regulated entities as proposed by [79].

Besides the computational complexity, performing multi-optimization equilibrium modeling requires extensive information as the portfolio of each simulated entity, the fundamental determinant of market power, needs to be defined. Therefore, it is more often that studies are based on a testing pseudo-market [55, 84, 86] than a real market [78].

Exogenous price vs. price as a function of decisions

With a single-optimization approach, the upper level problem, i.e. market clearing, becomes an exogenous progress. The output of market clearing, price (and volume as well which is however rarely considered in literature), is an fixed input to the single-optimization model. In this way, the decision making entity is virtually a price taker as its decision will not affect the price.

An alternative way to internalize the price formation is to make the price as a function of decision variables rather than being constant. However, such a method will make the optimization become non-linear since the objective function is often the product of price and decision variables. The function has to be simple. For example, Sioshansi *et al.* [57, 90] used the simplest linear function for price and performed the optimization with a quadratic objective function. Due to this limitation, recent research works would turn to the equilibrium model as is introduced earlier to study situations with price makers.

Overall, although there is an abundance of literature studying price makers with flexibility, these methods were seldom applied for estimating real market values, which is however of most interest to us. Therefore, a pragmatic approach is to assume all participates are price takers. This assumption is definitely true when the market is perfectly competitive. Or according to the study based on actual market conditions in Germany [78], if energy storage capacities are allocated to generators reasonably (in line with their generation market share), total revenues from all players would remain almost unchanged whether dominate players act as price makers or price takers. Since we are primarily focused on the value of market as a whole rather than for each individual player, a price taker approach without considering the strategic interaction between players might suffice our needs, as is revealed by literature. Furthermore, perfect competitive market is not an exorbitant assumption and results based it shall anyway provide a decent reference.

2.2.2 Predicting the price

With the approach of single-optimization modeling using exogenous price, price is a crucial input to the optimization problem. It is of great importance how the price is obtained and how much foresight the decision makers have on price.

Actual price signal vs. simulated price signal

Some studies used real market data for valuation [56,57,59–62,64]. The merit of this approach is that they can provide the most accurate estimations although in a retrospective sense. The value will not depart significantly in short term since the power market was empirically found to stay relatively stable year over year, unless some exceptional events happened, e.g. the shale gas revolution in the US leading to drastic drop in electricity price around 2008 [45, 64]. However, those estimations cannot remain valid in the long run. Moreover, increasing renewable penetration is accelerating the changes [91–97]. For our study, this reveals the main drawback of using real market data being that it is not sufficient to provide long-term guidance, and the short-term view has to be renewed frequently. For research works that are concerned less on long-term scenarios such as the studies that just need to perform valuation for proof-of-concept, there is another issue. Directly using historical data as input eliminated the uncertainty of price together with associated risks. Therefore, many studies developed auxiliary simulation models to generate price scenarios in complemented to the main optimization program. For example, Grunewald *et al.* [98] adopted a merit-order model to simulating wholesale electricity price setting behavior, thereby being able to generate price scenarios in the long run with changed generation mix as inputs for energy storage valuation. What are more commonly implemented by academic studies, as is mentioned, are simulating price uncertainties in order to perform risk assessment. Seasonal autoregressive integrated moving average (SARIMA) is one of the most commonly used models to simulate the stochastic processes of electricity price [99–102]. SARIMA model can be denoted as $(p, d, q) \times (P, D, Q)_s$. The terms (p, d, q) represent orders of autoregression, differentiation and moving-average respectively while $(P, D, Q)_s$ correspond to orders of the seasonal part. Alipour *et al.* used a ARIMA $(2, 0, 2) \times (2, 0, 1)_s$ with seasonal part being AR (24,168) and MA (168)[1] in this study where the profits of EV aggregators were assessed. Similarly, Mahmoudi *et al.* [101] implemented a ARIMA $(6, 1, 3) \times (1, 0, 0)_s$ with seasonal MA (168)[2] to generate price scenarios for a stochastic program of DR aggregators. These stochastic models are estimated from historical data so cannot be applied solely to perform long-term forecast with changed generation mix.

In our study, both approaches using real market data and developing auxiliary price simulation models are applied, to estimate the market value under current market conditions and understand the impact of possible changes of market conditions (increased RES penetration) respectively. For the price simulation model, the merit-order model and stochastic SARIMA model and synergized, which will be discussed in detail in Chapter 4.

Perfect foresight vs. limited predictability

While historical data is directly used as input to the optimization, it contains an assumption that the decision maker has perfect foresight of the future price. This is the case of the studies mentioned previously [56, 57, 59–62, 64]. The perfect foresight assumption leads to overestimation of the value compared to what can be captured in reality [69].

Applying the stochastic price simulation as is introduced previously is certainly a powerful way to resolve the issue. However, the stochastic approach adds complexity and requires more computation time, so determinate approach is still favored in most cases. Therefore, some researchers ran sensitivity analysis to evaluate the level of overestimation caused by perfect foresight. Several authors applied methods such as reducing the forecast window [58] or using back-casting techniques, i.e. determine the future dispatch plan with historical data [57, 103, 104]. It was found that 60-90% of the value with perfect foresight can be realized using primitive statistical price forecasting techniques. In reality, it is possible that players can apply some advanced forecasting techniques to make the value close to the ideal value obtained with perfect foresight.

Therefore, the approach with perfect predictability is still useful to provide reference values indicating the upper bound. Sensitivity analysis might be necessary by reducing the predictability.

[1] The time step in this study is 1 hour. Therefore, 24 corresponds to the length of a day and 168 corresponds to the length of a week. The seasonal part is designed to capture the daily and weekly seasonality.

[2] The time step is also 1 hour so 168 represents weekly seasonality.

2.2.3 Stacking technologies or applications

Although many studies are carried out with one technology for one application, it is typically more complex in reality. Several technologies can be jointly organized and dispatched to provide more than one types of services at the same time. These operating models may shift the profitability with a larger optimization space.

Hybrid system

A number of researchers studied the cases with hybrid systems, which are typically a combination between RES generation and one or several flexibility resources. While conventional research works were mainly focused on the large-scale wind and storage at one site [74, 104], increasing studies were carried out recently from the perspective of aggregators. Han *et al.* [105] studied the optimal trading strategy of a VPP operator with distributed generations (wind power), energy storage and flexible load (load shifting). Calvillo *et al.* [106] investigated both panning and dispatching strategy of VPPs with photovoltaic (PV) systems, heat pumps (HP), batteries and demand response (load shifting) in Spanish wholesale energy market. Xu *et al.* [107] researched the optimal bidding strategy of aggregators with distributed generation, EVs and inflexible loads taking into account risk aversion.

Referring to these studies, the most challenging issue to port this approach to our study is determining the optimal portfolio mix of the system. Among the articles mentioned above that are purely in micro-perspective, only the one authored by Calvillo *et al.* [106] studied the optimal planning by referring to methodology developed for microgrid (MG) operators [108]. For works focused primarily on operating and trading strategy, sizes are assigned arbitrarily to each technological sub-systems. For our study seeking to obtain the maximum value of the whole market, designing the optimal system mix for the whole system will be overwhelming and is virtually a task of grid planner, so it is not considered. Instead, we would conduct separate investigation for each of the selected technologies.

Multitasking

In contrast to hybrid systems, a more common exercise of stacking is multitasking, i.e. offering several services at the same time. A typical combination of services is arbitrage plus frequency regulation. While some authors argue it is a necessary measure to make flexibility management solutions profitable [69, 109], we view it as a natural choice: most of the flexibility management systems have to participate in the wholesale energy markets in order to sell their bulk generation or fulfill their bulk demands; based on this prerequisite, while players plan to supply frequency control services that are normally more precious, they would naturally go for multitasking. Such type of works are observed in studies on energy storage [59, 62, 109], EV2G [102, 110–112] and less usually DR [113].

Multitasking is performed and tested in our study.

2.2.4 Formulating the problem

Deterministic modeling vs. stochastic modeling

In our studies, there lie many factors that are uncontrollable or not fully predictable. Besides the price in power markets that has been discussed already, there are still several key stochastic terms that are often encountered in studies related to flexibility management:

- The generation of variable RES such as wind and solar, and
- Frequency control signal from system operator, and
- End-users' behavior and thus availability of demand response.

Stochastic modeling would be helpful in cases where this terms are involved. Strictly, the objective function of an optimization with a stochastic approach is maximizing the expectation of value in different scenario and formulated as: [69]:

$$\max_{x \in X}\{f(x) \equiv E[F(x(\omega), \omega)]\}$$

where, $x \in \mathbb{R}^n$ is the vector of decision variables, $\omega \in \Omega$ is the vector for the stochastic terms, and F is the objective function.

The articles authored by Qin *et al.* [114] and Xi *et al.* [115] are formulated in this way. It is worthwhile to mention that in the paper by Qin *et al.* [114], only the uncertainty of price was considered while the frequency control signals are treated as deterministic.

Nonetheless, most of the studies on flexibility management with stochastic approach are virtually scenario-based determinate programming. Their objective function is to maximize the objective value for each scenario and formulated as:

$$\max_{x \in X}\{f(x) \equiv F(x(\omega), \omega)\}$$

where, $x \in \mathbb{R}^n$ is the vector of decision variables, $\omega \in \Omega$ is the vector for the stochastic terms, and F is the objective function.

Such a problem formulation is used in [85, 101, 102, 105–107, 116]. More specifically, Zhang *et al.* [85] considered the uncertain outputs of distributed generation (DG). Mahmoudi *et al.* [101] use a random Boolean indicator to represent the participation of DR customers. Xu *et al.* [107] studies a system with DG, DR and EV but particularly focused on the EV uncertainty with the arrival/departure time, driving distance sampled randomly from historical probability distributions. Uncertainty of frequency control signals was modeled by Alipour *et al.* [102] where the randomness of price and EV availability are considered as well.

In works where multiple stochastic terms are considered, a multi-stage scenario-based optimization was applied [102, 105].

Nonetheless, stochastic approach is not a must [69]. Using the determinate approach for the most likely scenario is sufficient to provide a decent reference value compared to the result from stochastic programming, as was illustrated by [106]. The most important merit obtained with stochastic approach in addition to results using determinate approach is risk control.

In our study, we apply the determinate approach for most of the time. Scenario-based optimization is performed only in cases where the stochastic price simulation is involved.

Linear programming vs. non-linear programming

Non-linearity is not favored in optimization which would significantly reduce the computation tractability and is likely to make the optimization non-convex.

In the studies we have reviewed, non-linearity may be introduced in various ways, including:

- The upper level market clearing problem in the multi-optimization equilibrium models is usually not linear. [55, 79, 87–89]

- Non-linear relations may exist between cost and decision variables [101].

Typically, researchers would seek measures such as the primal-dual approach to convert the non-linear programming to be mixed integer linear programming [55, 85, 87, 117] or tried to approximate the non-linear objective function using a piece-wise linear function [101].

In our study, we avoid to include of non-linearity in our optimization. Any relations that may cause non-linearity such as the price formation are made out of the optimization.

Since our perspective does not perfectly in most academic articles, there does exist a perfect valuation framework that can be directly port into our study. Therefore, we mapped a number of research papers with different approach and selected the proper ones considering both effectiveness and computational tractability.

Chapter 3

Power Markets and The Role of Flexibility 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: a comparative analysis

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. [18] 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. [100]

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.

3.2 Proposed business model

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

3.2.1 Offering

3.2.2 Customer

3.2.3 Application

Chapter 4

Methodology for Quantitative Valuation of Flexibility Management Markets

This chapter presents the methodology for quantifying the value of flexibility management 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 significant 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 redundancy 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 variable 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

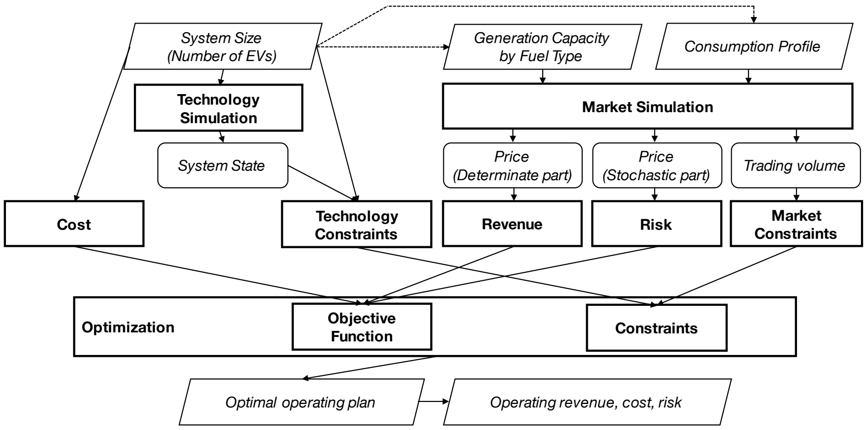

Figure 4.1: Flow chart of the techno-economic model

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 4.2.2.

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

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

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 $j \in J$.

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

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

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

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

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

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 [102] and DER [105], as well as for conventional energy trading companies [118], 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 [119], 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 [119]:

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

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:

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

4.2.2 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 [66] [65] 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) [120] [98]. 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 preliminary based on work done by [98] 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 [98], 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 [121]. In case of peak period, C_t^g represents total available generation capacity of class g and P_t^g is the output of generation 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 [40] (Figure 4.2.2):

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

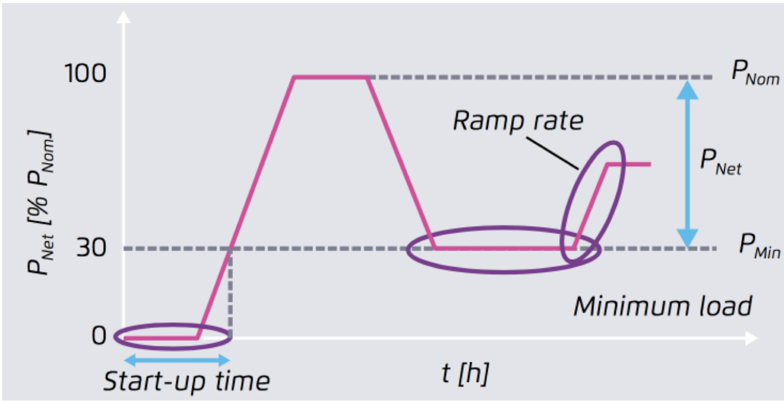

Figure 4.2: Qualitative representation of key flexibility parameters of a power plant [40]

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

If a power plant can adjust its load from zero to nominate capacity within a time block in the day-ahead market (typically 1 hour), it can be deemed with infinite flexibility in the day-ahead market. This applies to most type generations including solar, wind, hydro and electrochemical systems, etc., except for generations using steam turbines [40], including nuclear, coal-, oil and gas-steam, etc. The gas turbines can be ramped up to full capacity within typically 30 minutes [122] [123] so can be considered as flexible generation.

For a steam-turbine power plant, the minimum operational load is about 25-60% of its nominal capacity while the time required to start from standstill is longer than 2 hours [40]. 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 4.2.2:

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

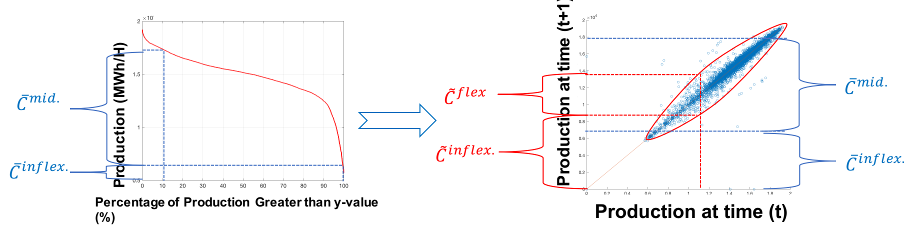

Figure 4.3: Schematic illustration of determining bounded flexibility for limited flexible generations

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 [84]. There are significate dependences of the real-time (intraday, balancing) energy price on day-ahead price [24]. 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.

4.2.3 Market constraints

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

Generally, these constraints can be formulated as

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

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

4.3 Technology-based modules

4.3.1 Cost module

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

Operation-independent costs

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

The initial capital cost for a storage system can be divided into two components: an energy-based component, approximately linear to the energy capacity of the system (denoted $\overline{s}$, in MWh), and a power-based component, approximately linear to the power rate of the system (denoted $\overline{r}$, in MW) [109]. 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 [42].

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 [66]. 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 [66]. 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 [124].

However, as has been reviewed and analyzed in [109], 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. [124]

- 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. [109]

Degradation costs can be neglected while operating life time is longer than designed life time, which is generally valid for non-battery energy systems [60] [63] [58]. Some research works studying battery system also made the same assumption [59] [61] [57]. 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 [109]. Nonetheless, it was also pointed out by [109] 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 [59] [62].

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

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

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

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

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

It can be noticed that when a virtual arbitrage is conducted where some $e_t^{d,i}$ and $e_t^{c,i}$ are offset, it will activate the degradation damping with Equation (4.28) while there are no real physical processes causing degradation. This will be corrected in final profit calculation but in decision making process using optimizations we keep it as it is intended to restrict the virtual arbitrage.

Similar to Equation (4.10), we reconstruct the diagonal matrices with the decomposed ratios from Equation (4.29) and (4.30).

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

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

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,

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

$I_{T\times T}$ 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.

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

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 storage:

- The availability of an EV2G system, in terms of delivering both energy (in MWh) and capacity reserve (in MW), is dynamic rather than static, since the number of EVs connected in the power grid is changing all the time with the behaviors of plug-in/ plug-out.

- The energy stored in the system will be consumed not only for delivering our targeted services (arbitrage or balancing), but also for driving of EVs themselves. This part of costs will be implicitly captured by the revenue module using Equation (4.1), which will distort the real value of services provided for the grid.

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

1. The EV2G system is modeled as a dynamic ESS by taking into consideration the connection/ disconnection of EVs to/ from the grids.
2. The costs of energy consumed for driving are accounted and analyzed separately

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

In order to transform the model for ESS to be dynamic in size and availability, we introduce additional terms to represent the number of EVs entering (n_t^+), leaving (n_t^-) and remain in (n_t) the system at each time step.

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

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

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

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

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

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

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

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

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

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

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

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

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).

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

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

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.

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

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

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

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

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

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

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

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

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

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

The constraints of storage are formulated as:

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

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

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

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

Electric vehicle to grid

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

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

where, N is determined by Equation (4.40).

4.4 Optimization Engine

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

The objective function of the optimization problem is formulated as:

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

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

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

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

4.5 Addtional measures for special cases

4.5.1 Backcast technique to reduce the predictability of price

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

In this thesis, although the players would suffer risks of uncertain price movement with the introduction of stochastic part of price, they were still assigned with full foresight of the probability distribution. One may argue this is also unrealistic and could probably over-estimate the market potential. Therefore, by extending the work [103] and [57], 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 [105] or deny reserved biddings between day-ahead and real-time market [62].

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 [109] [125] [126] [127] 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" [128]. 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. [128] [129] 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. [68]

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. [130] 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. [26]

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. [68]. This issue is currently under discussion in Special Market Implementation Committee meetings.

DR emergency fast changing over years [45] 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 resource, e.g. the performance & historical performance, benefits factor, mileage, 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 geographies.

5.2 Quantitative studies and results

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

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

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

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

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

Two types of works were carried out. We first examined the value of markets for flexibility management under current market conditions, i.e. based on historical observations without involving the market simulation module (Section 4.2.2). This allows us to obtain some concrete numbers to establish a comprehensive understanding toward the value of flexibility management in nowadays' power markets.

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

5.2.1 Data, parameters and valuation metrics

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

For cost determinations, we would first use figures based on the present market pricing level, and then make scenarios with reduced costs to find the break-even point if it is not yet profitable. According to the International Renewable Energy Agency (IRENA) [131], the cost for battery energy storage systems was analyzed as proportional to their energy capacity, $\overline{s}$, and the energy cost coefficient, C^s, for state-of-the-art lithium-ion batteries were reported to be ca. $\$350/kWh$ in 2016. The replacement cost were based on actual price from Tesla [132]. The operating life is set to be 6000 FCEs, which corresponds to an optimistic estimation by Sandia National Laboratories [67]. Designed life time is assumed to be 10 years. Discount rate is made as 10% as is discussed in Section 4.3.1. The technology costs were made to be zero so that the derived profits will be the margins that can be possibly realized by technology vendors. All the parameters for cost calculation are summarized in Table 5.1.

Table 5.1: Parameters for cost calculation

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

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

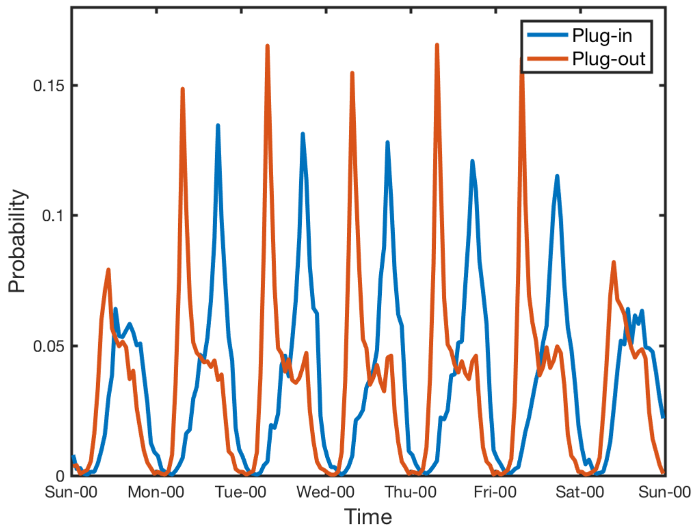

Figure 5.1: Probability of EV plug-in/ plug-out

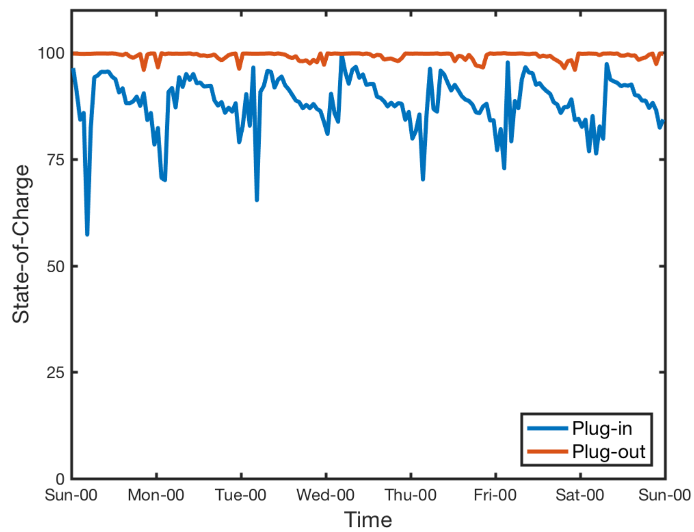

Figure 5.2: Average SoC of EV when plug-in/ plug-out

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 [133] 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 [134].

Simulations are then performed to get EV driving profiles, which are based upon data from the California Department of Transportation's California Household Travel Survey for 2010-2012 [135]. This survey carried out multiple objectives and included 79011 vehicles. For our work we focus on a proportion of the vehicles, 2910, which were fitted with GPS. These vehicles were monitored continuously for a 7-day window with the 1-second resolution. The GPS data is then processed into trip profiles, while include information of the location of each EV at each time step as well as the trips made by each EV. Furthermore, together with the parameters of the EV model we have selected above we simulated the SoC time series of the EV batteries. Finally, from the simulated results, we can statistically derive the value of probability distribution of EV plug-in n^+, plug-out n^-, and average state-of-charge (SoC) of batteries plug-in s^+, plug-out s^-, as introduced in Section 4.3.2. The results are shown as Figure 5.1-5.2 where we can see clear periodic patterns that are different between weekdays and weekends.

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

- **Revenue:** the total explicit revenue from electricity markets calculated as Equation (4.1) in Section 4.2.1, per annum
- **Operating cost:** the operation-dependent costs (essentially degradation cost); refer to Section 4.3.1 and Equation (4.28), per annum
- **Operating Profit**: the total revenue net of the operating cost, per annum
- **Fixed cost:** the equivalent annual cost (EAC) of operation-independent costs (essentially expenses on ESS infrastructure); refer to Section 4.3.1
- **Profit:** the total revenue net of both operation-dependent and fixed costs, per annum
- **Profitability ratio**: the ratio between the profit and overall costs including both operating and fix 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 are listed separately. Depending on the specific business model in practice, a portion of the implicit charging cost may be recovered by the technology vendors from the end-users, although in this thesis we did not exclude it from calculating the profit. As a result, the criteria are altered as:

- **Revenue:** the total explicit revenue from electricity markets calculated as Equation (4.1), per annum
- **Operating cost:** the operation-dependent costs (essentially degradation cost), per annum
- **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, per annum
- **Profit:**: revenue net of costs including the implicit charging cost and battery degradation. The investments on technology are made to be zero as is discussed at the beginning of this section, per annum
- **Profitability ratio**: the ratio between the profit and overall costs including both operating and implicit charging costs

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

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

Two the most crucial states are:

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

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

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

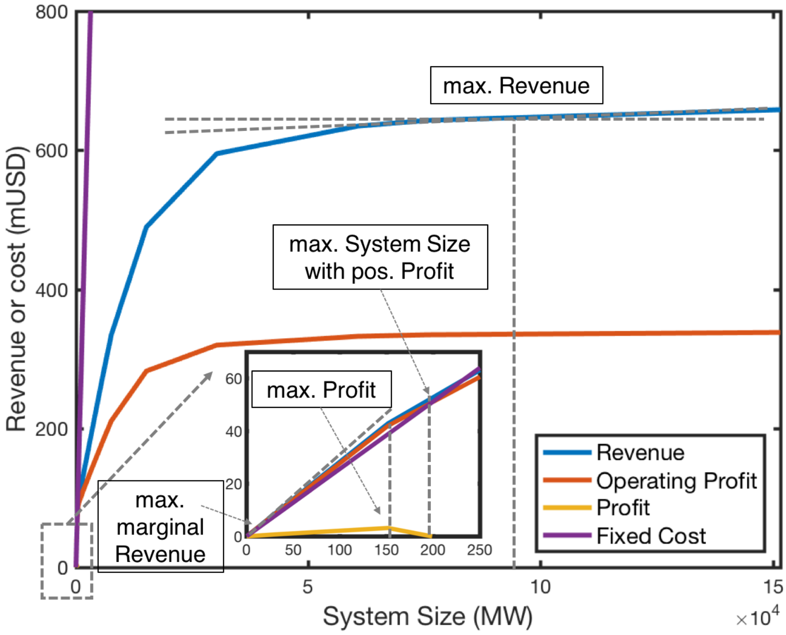

Figure 5.3: Graphic illustration of 4 scenarios

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

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

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

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

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

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

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

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

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

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

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

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

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

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

Finally, we would normalize results with respect to the overall scale of the market, in order to make cross-regional comparison more intuitive. The main metric to represent the scale is the average consumption rate (in MW) in the whole market. Consequently, values of cash flows would be shown in unit of million USD per year per MW consumed (USD/(a · MW)). Meanwhile, the metering point (MP) is taken as a auxiliary metric and would be mentioned in certain circumstances as it represents the number of end-consumers in a market. The average consumption rates were obtained from the power markets data in 2016 and the statistics of MP are provided by commercial market data provider, Northeast Group [136] [137] [138]. All the relevant numbers are listed in Table 5.2.

The currency exchange rates are determined as the real market data as of January 1st 2018, when 1 EUR is equal to 1.20 USD and 1 AUD is equal to 0.78 USD [139].

5.2.2 Valuation of markets under current market conditions

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

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

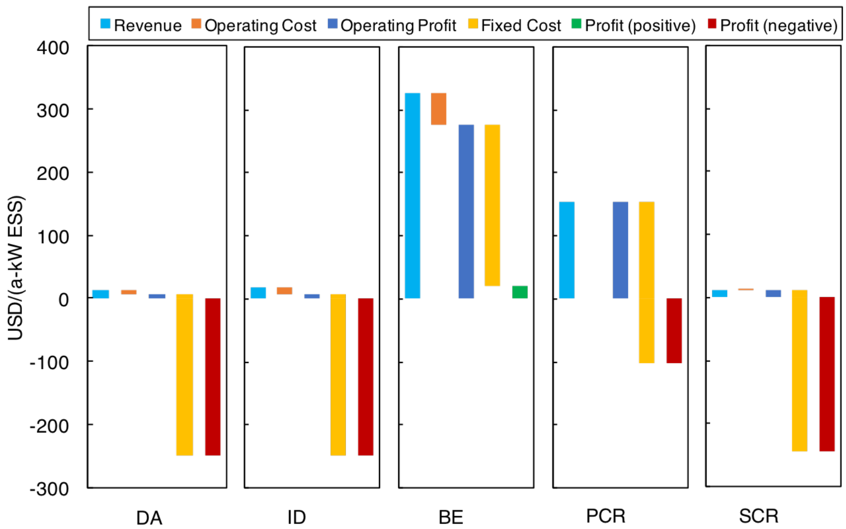

Figure 5.4: Profitability of ESS in Germany electricity markets in the scenario of “max. marginal Revenue”

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

Meanwhile, with ample size of ESS, maximum potential market sizes can be derived, corresponding to the scenario “max. Revenue”. Summarized by Figure 5.5, annual cash flows are shown per MW consumption as normilzed values to the overal average consumption, 59 138 MW . For example, the normalized revenue for arbitrage in day-ahead market is 4041 USD per year per MW consumption, which indicates the achievable revenue for a power

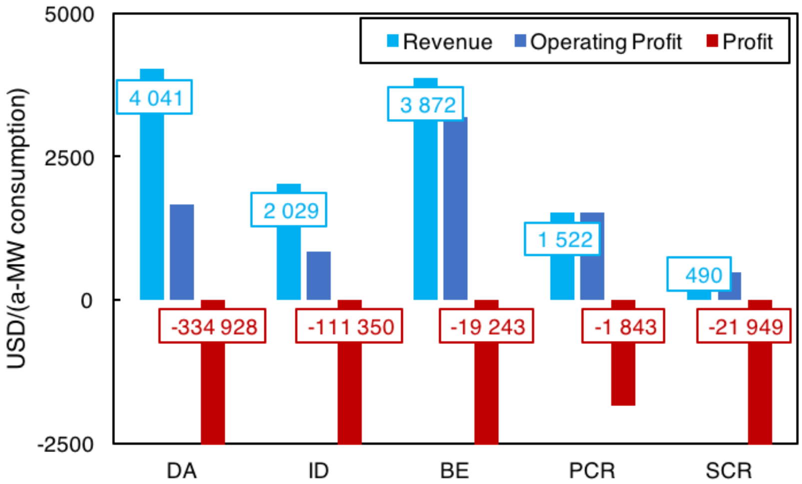

Figure 5.5: Market size of ESS in Germany electricity markets in the scenario of "max. Revenue"

system in Germay with 1 MW average load and corresponds to 239 mUSD/a in whole German market by mutiplying the base of 59 138 MW.

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

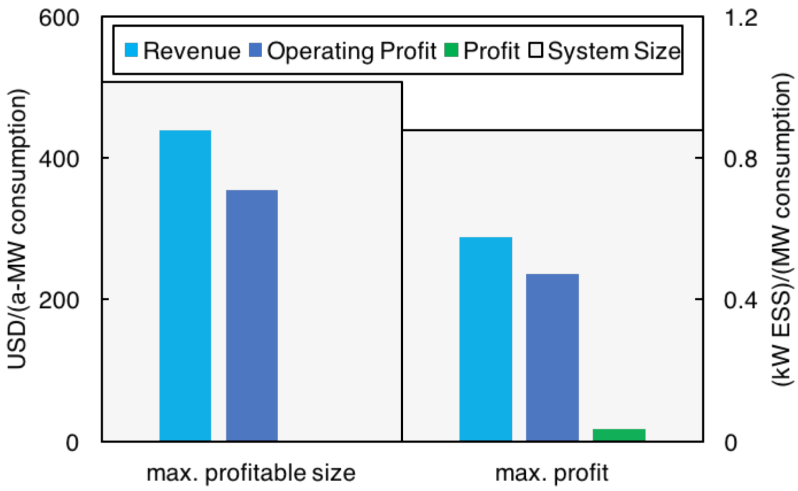

Figure 5.6: Market size of ESS in Germany electricity markets in the scenario of "max. System size with pos. Profit" and "max. Profit"

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

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

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

However, we may argue this situation shall not be long-lasting. We have already seen that certain amount of BESS will be a cheaper option to defer the expense on imbalance settlements compared to what are currently incurred. The market operators shall develop well-designed frameworks to encourage the participation of these resources that are beneficial to lower the overall system costs. In reality, there are indeed debates proposing possible solutions on this issue, e.g. letting TSOs who have the most abundance of information own and dispatch the storage resources [79], re-engineering the pricing mechanism of balancing energy [26] and implementing favorable frequency control products for storage [109], etc.

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

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

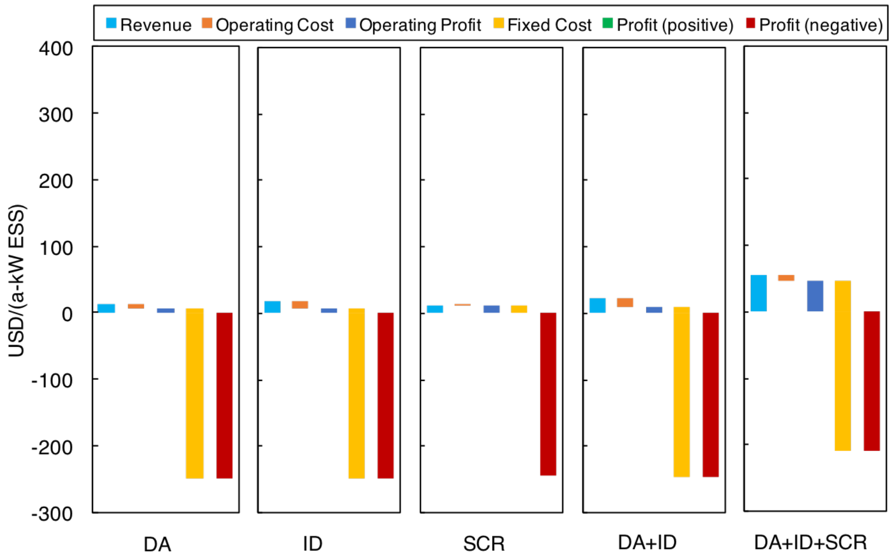

Figure 5.7: Profitability of ESS with multitasking in Germany electricity markets

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

While there are no significant synergies observed between day-ahead and intra-day markets (the unit returns remain unchanged in the scenario of maximum marginal revenue), stacking secondary control reserve with these two energy marketplaces will significantly improve the unit revenue (from 11 and 22 USD/(a · MW) to 54 USD/(a · MW)) as well as the maximum revenue potential (from 6426 USD/(a · MW) plus 490 USD/(a · MW) to 8725 USD/(a · MW)). The maximum unit operating profit, as a consequence,

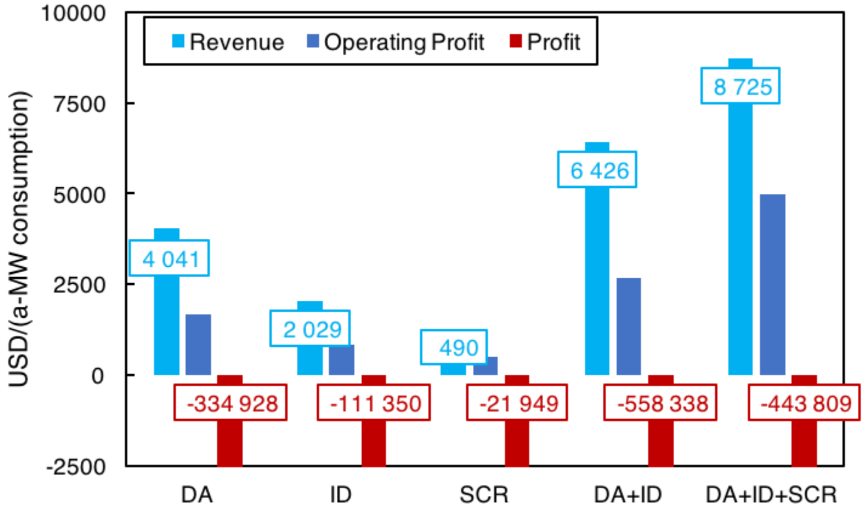

Figure 5.8: Market size of ESS with multitasking in Germany electricity markets

raises by 4.5 times. The increment of maximum potential revenue of 2299 USD/(a · MW) by stacking SCR on DA+ID indicates an additional revenue of 1809 USD/(a · MW) are accessible for ESS in the SCR markets, reducing the intangible part from 83.5% to 22.7%. This corresponds to our previous analysis that the non-energy-neutral signal is indeed an issue for BESSs and has to be neutralized externally. Nonetheless, coping with third-party energy transactions requires the BESSs spare certain capacity to receive or release the energy, which reduces their availability in delivering SCR services. This is reflected on the result that this case with multitasking is still not profitable.

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

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

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

As we can clearly see, the RegD marketplace that is specially designed

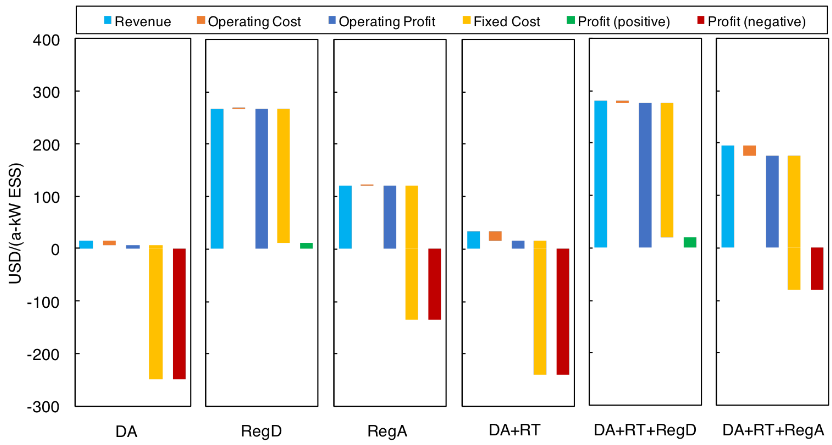

Figure 5.9: Profitability of ESS in PJM electricity markets in the scenario of "max. marginal Revenue"

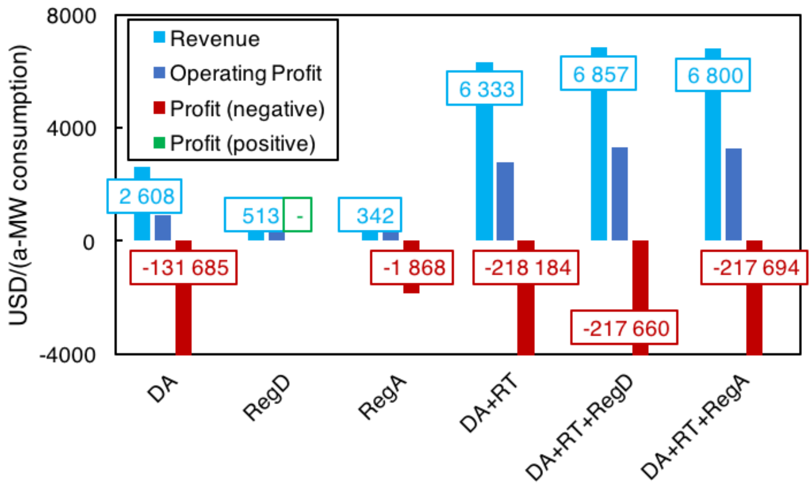

Figure 5.10: Market size of ESS in PJM electricity markets in the scenario of "max. Revenue"

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

Those merits allow BESS players to offer RegD alone without coupled operations in the energy market which is currently necessary in Germany's power markets. As a result, stacking it with the energy market does not

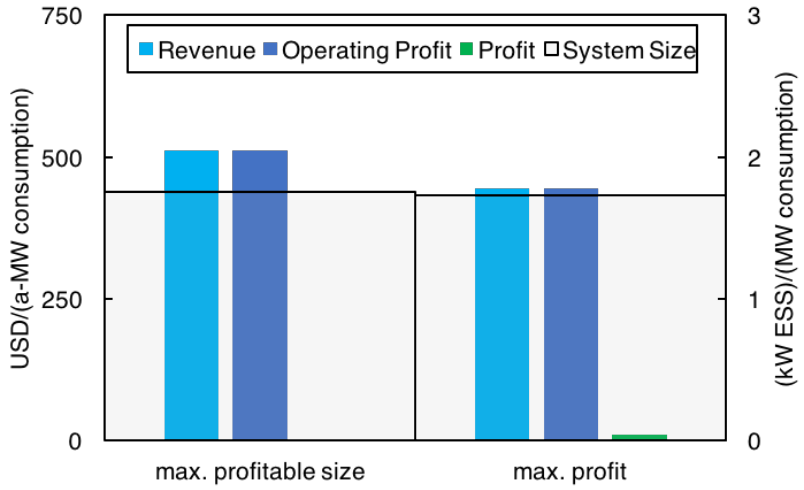

Figure 5.11: Market size of ESS in PJM electricity markets in the scenario of "max. System size with pos. Profit" and "max. Profit"

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

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

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

Overall, PJM shows a perfect example on how to offer incentives for the emerging storage technologies that are beneficial to the system, by implementing proper market frameworks such as the RegD and the emergency DR program. For technology vendors, this market is already quite mature

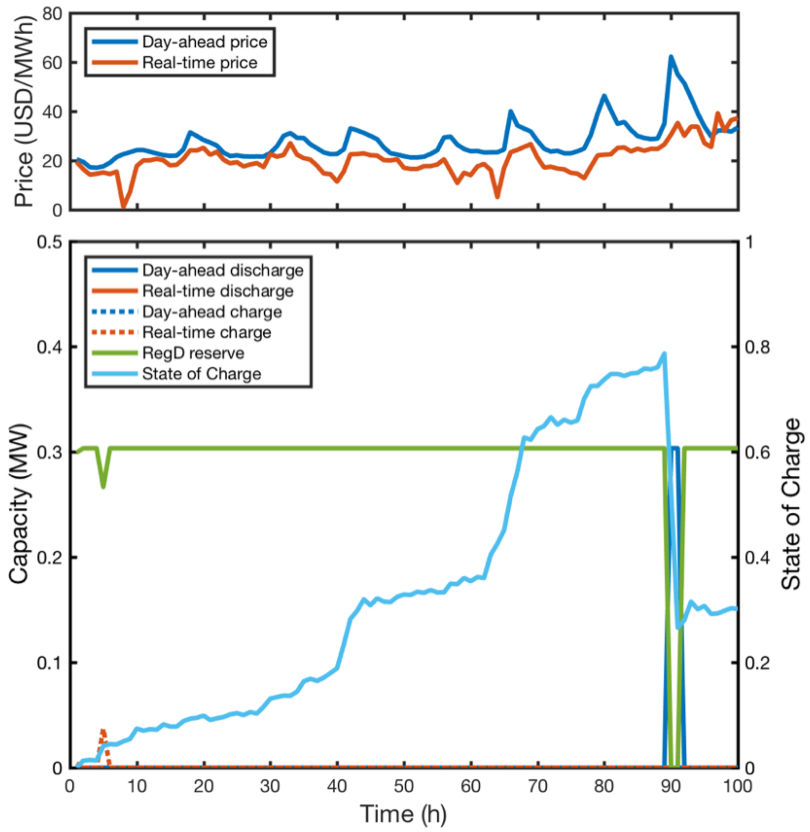

Figure 5.12: A example of operational plan with a 0.3MW battery energy storage system

without spare space for new entrants unless significant changes may occur on market conditions, e.g. vast renewable penetration. Nonetheless, existing business cases in PJM may offer viable references for technology vendors to conduct similar practices in other markets. The upper-bounded values indicating the market potential are summarized in Table 5.8.

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

In New South Wales power markets, we only studied the real-time energy market, which was primarily due to the limitation of data availability. Only information about total payment are available for the frequency control products. However, it was found that the overall size of these unaddressed markets are indeed negilible compared to the real-time energy market. The total payment in NSW's frequency control ancillary service (FCAS) market was worth 23.4 mUSD (2933 USD/(a · MW)) in 2016, which was equal to just 0.53% of the total payment in the real-time energy market that was

4.4 bUSD (551 516 USD/(a · MW)). It was also much smaller than merely the arbitrage value, being 2.7% of the revenue from arbitrage of 109 301 USD/(a · MW) as shown by Figure 5.14. This reflects the philosophy of market design to fully exploit the ability of real-time energy market to response to the system imbalances which are otherwise tackled by frequency control markets [140] [61]. As a result, the price volatility in NSW's real-time energy market is significantly higher than the energy markets in other geographies, as is shown by Table 5.3.

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

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

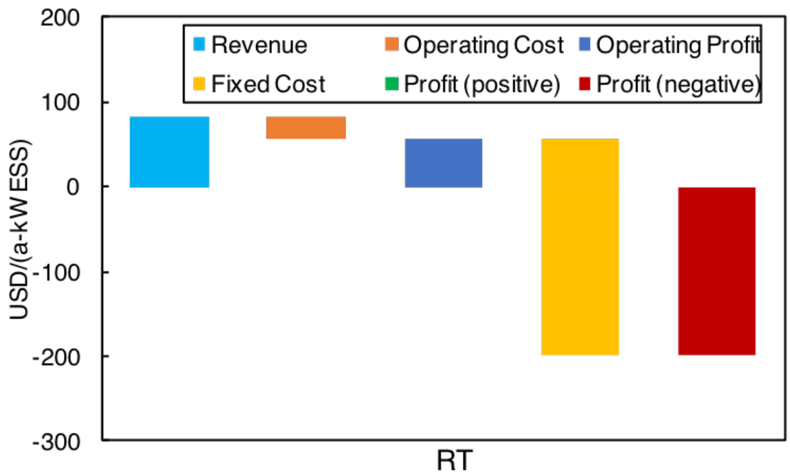

Figure 5.13: Profitability of ESS in NSW electricity markets in the scenario of "max. marginal Revenue"

Such a volatile market is favorable for arbitrage. As we can see from Figure 5.13 and 5.14.Profitability-wise the marginal revenue per unit system, 83 USD/(a · kW ESS)) is 2.4 times the value of arbitrage in DA+RT in PJM and 3.8 times the value of arbitrage in DA+ID in Germany. In terms of market potential, the maximum arbitrage revenue 109 301 USD/(a · MW)) is roughly 17 times higher compared to either of those two arbitrage cases in Germany and PJM.

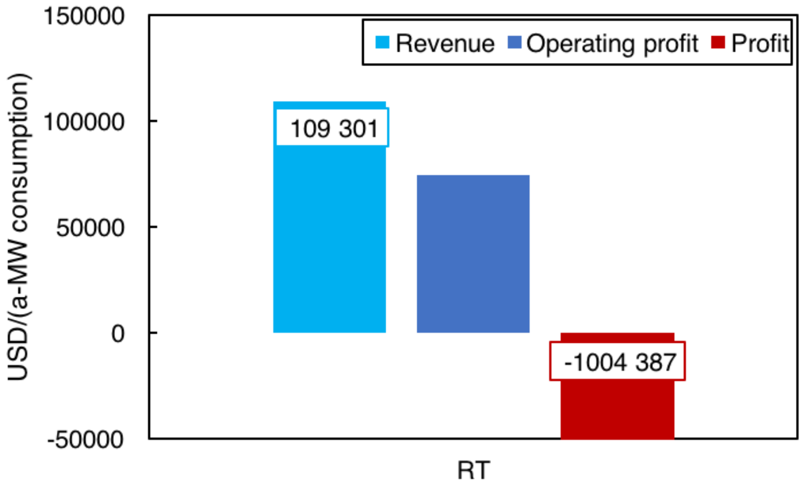

Figure 5.14: Market size of ESS in NSW electricity markets in the scenario of "max. Revenue"

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

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

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

In each geography, the case with the highest arbitrage potential was selected, which is respectively arbitrage in coupled day-ahead and intra-day market in Germany (DA+ID), arbitrage in coupled day-ahead and real-time market in PJM (DA+RT), arbitrage in real-time market in NSW (RT). We would show the maximum profitability ratio that is realized by a small size of BESS. Meanwhile we would present the profitable revenue that is obtained as in the scenario of "max. System Size with pos. Profit" to the maximum potential revenue derived from the scenario "max. Revenue". It shall be pointed out the maximum revenue that is independent from costs would remain constant so adopted as the cardinal term to illustrate the growth of profitability.

Figure 5.15 - 5.17 illustrate how the profitability and market size will evolve with cost reduced by up to 95% in three geographies. The break-even

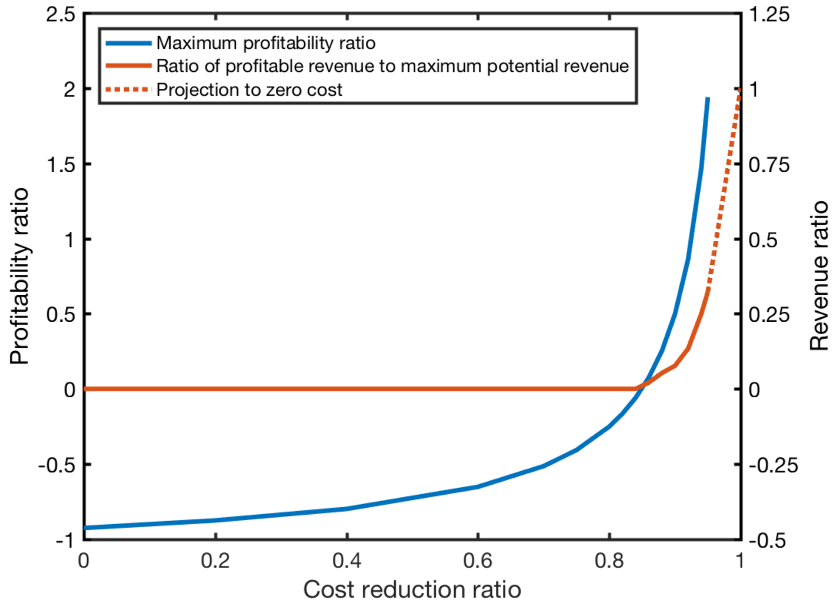

Figure 5.15: Development of market size and profitability of arbitrage in coupled day-ahead and intra-day markets with reduced costs in Germany

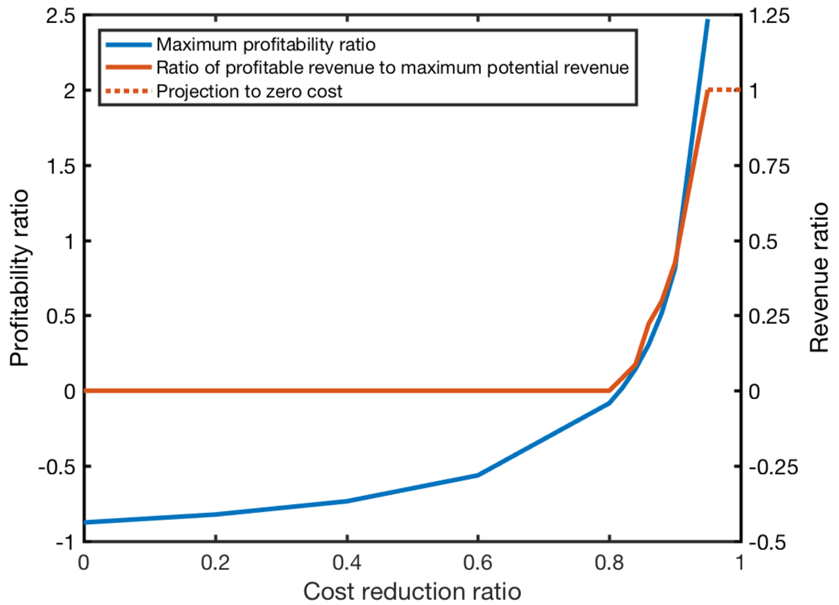

Figure 5.16: Development of market size and profitability of arbitrage in coupled day-ahead and real-time markets with reduced costs in PJM

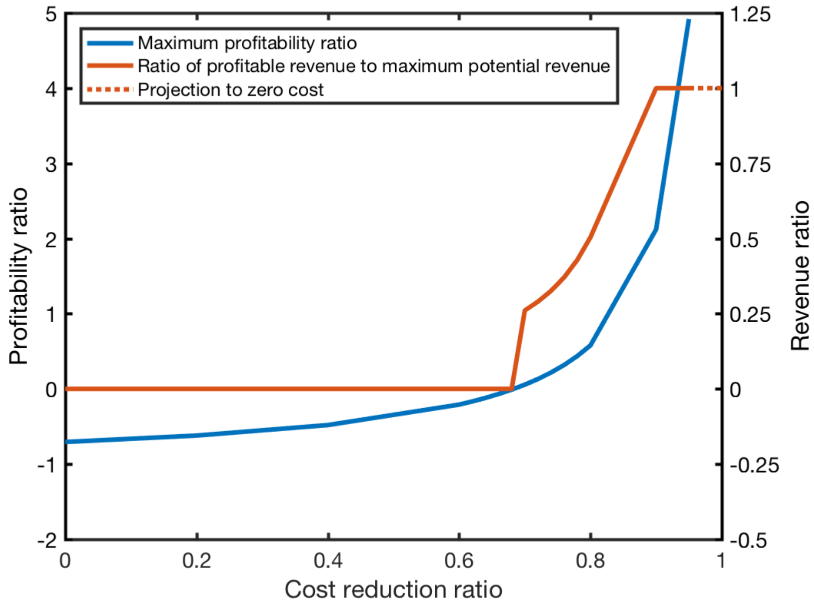

Figure 5.17: Development of market size and profitability of arbitrage in real-time markets with reduced costs in NSW

point of costs is found to be 84%, 81% and 68%, respectively in Germany, PJM and NSW. If we adopt the forecast made by IRENA [131] who predict the cost reduction by up to 60% by 2030, none of these markets will be profitable for arbitrage by 2030. Even if we applied a constant learning rate of 14% per annum according to [42], the break-even point will be realized in 12, 11 and 8 years, respectively in Germany, PJM and NSW.

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

As a conclusion, the cost reduction of BESS by learning effect alone will not turn over the profitability of arbitrage using BESSs in the near future. Unless revolutionary technical innovations happen, opportunities of arbitrage using BESS may only arise with drivers from the market, e.g. renewable penetrations, which are to be shown in Section 5.2.3.

EV2G in Germany: changeling in developing business model

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

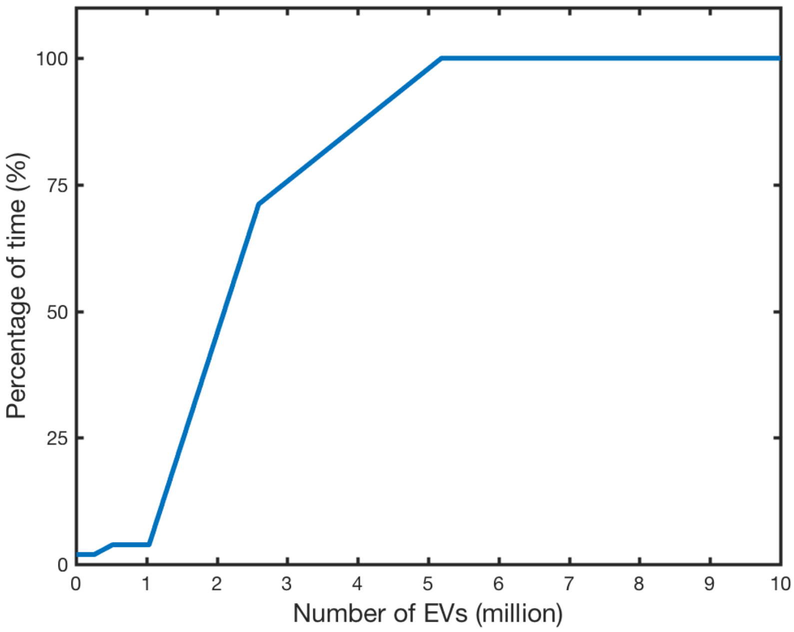

Figure 5.18: Percentage of time when EV charging demand cannot be fulfilled in Germany

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

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

- **EV number 2016:** assuming all EVs in Germany by 2016 are contract for delivering EV2G services
- **EV number 2017:** similar to the first scenario but using the data of 2017
- **2% market share:** assuming EVs will account for 2% of the total vehicle number in Germany (45 million according to [141]) i.e. 0.9 million EVs in the future

According to the Federal Motor Transport Authority of Germany (Kraftfahrt-Bundesamtes, KBA) [142], the number of plug-in electric vehicles has grown fast over the past year, especially in 2017. Since the EV registered before 2010 is negligible, we conceived the cumulative registration since 2010 as the total number of EVs in Germany, shown as Figure 5.19.

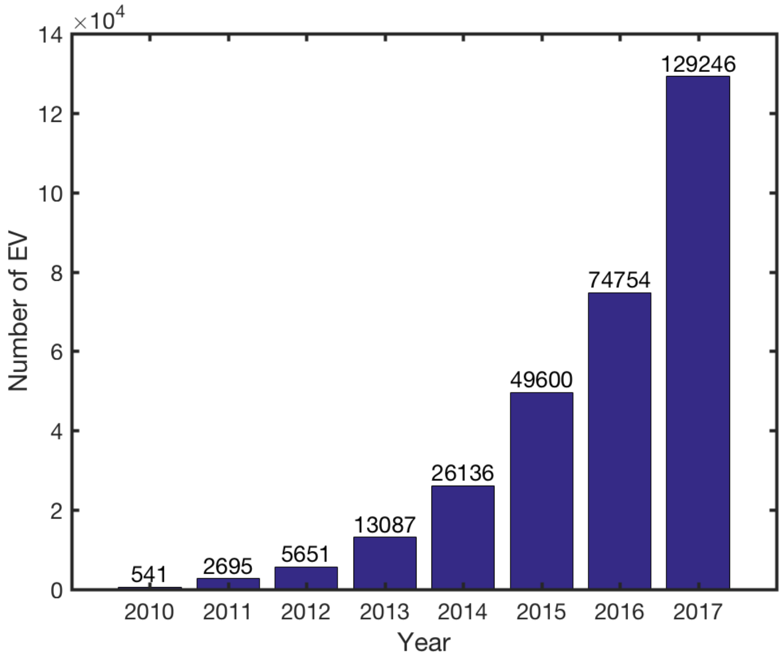

Figure 5.19: Cumulative registration of plug-in electric vehicles in Germany since 2010 [142]

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

Based on these scenarios, we performed the case studies and the results are shown by Figure 5.20. It was found that the arbitrage only in day-ahead market was not profitable at all, while arbitrage in both day-ahead and intra-day market was barely able to maintain a revenue-cost balance. The revenues captured from arbitrage was at most compensating the cost

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

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

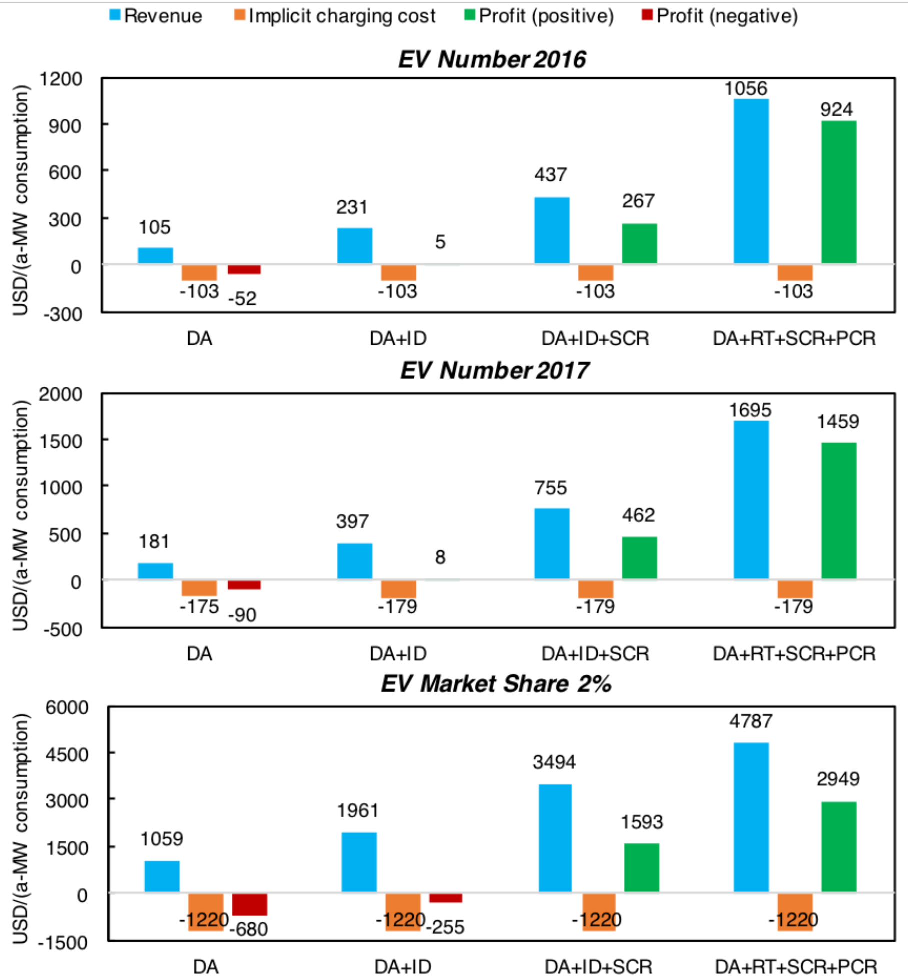

Figure 5.20: Market size and profitability of EV2G in Germany electricity markets

of EV charging. Profits would be possible if a business model where services providers could charge service fees from the end-users (EV owners). Although the service fees can be much lower than the normal charging costs for the end-consumers, it would be still challenging in practice to implement such a business model because the charging cost become implicitly embedded when a EV was used for V2G services. Overall, the low arbitrage values in Germany's energy market makes these business cases not appealing.

Coupling frequency control markets increases indeed the profits and it was found to be more promising with the drastic of EVs as there are still much more growth space till the scenario of 2% EV market share. However, it shall be noticed that our analysis has overlooked some factors which could make the business less profitable as shown here. The main issue is that we use a determinate approach to simulate the frequency control signal and EV driving behaviors which eliminated the risks of failing to deliver the frequency control services as planned. Alipour *et. al.* [102] 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 quantitative risk assessment against uncertainty is necessary for designing a specific project, it is beyond the focus of a study understanding the whole market value so is not included in our study. Besides, implementing EV2G for frequency control is not a mature technology due to its complexity [112] [86] [143] [144], which implies a high research and development cost.

It is also worthwhile to note that while the number of EVs (0.9 million) in the scenario of "2% Market Share" has reached the edge of the affordable level (1 million) for the grid, revenues are significantly smaller than the maximum potential revenues derived in the case studies of ESSs. The shares of maximum achievable revenue by EV2G to the total market potential by generic ESS were between 18-37% among different cases. This reveals that constrained by the limitations discussed above, EV2G will not be able fully cover the needs for flexibility by its own, even on a aggregated system level without considering the distributed manners. Other types of flexibility would still be necessary to complement the demands for flexibility in scenarios with high EV penetrations.

EV2G in PJM: RegD market would be saturated shortly if EV2G was indeed implemented

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

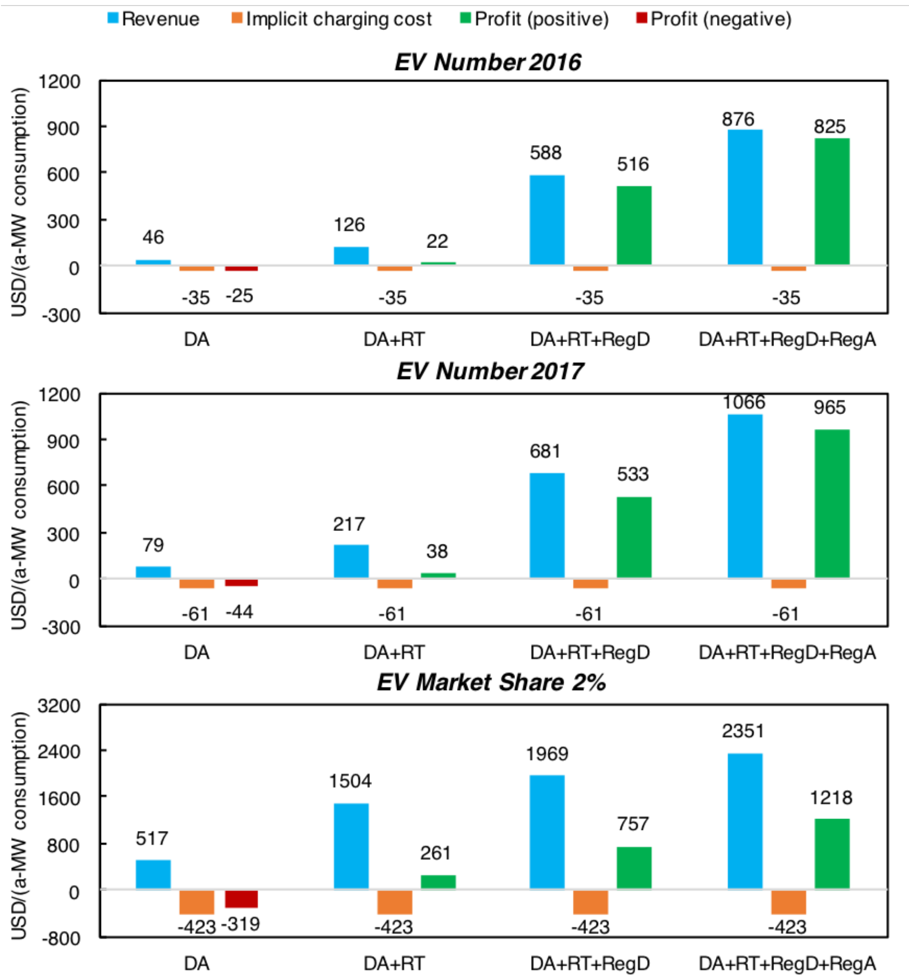

Figure 5.21: Market size and profitability of EV2G in PJM Electricity markets

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

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

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

Figure 5.21 summarizes the results of cases in PJM. Arbitrage in day-ahead market only was still not profitable. Coupled operations in real-time market lead to niche profits while the EV numbers are relative small, which is similar to the situation in Germany. However, with a 2% EV market share, we saw a profit from business case while it incurred loss in Germany's DA+ID markets. This can be explained by the PJM's real-time market as a hub for all real-time settlements has much higher liquidity than the intra-day exchange in Germany.

The incremental revenue by stacking RegD to DA+RT case was 462 USD/(a · MW) in the scenario of "EV Number 2016" while the addtional revenue by stacking SCR to DA+ID in Germany was merely 206 USD/(a · MW), which again reveals the favor of RegD toward flexibility resources.

Noticing that the whole RegD market potential for generic flexiblity resources is merely 513 USD/(a · MW) as was shown previously by 5.10. This market could be easily exhausted by a small size of EV fleet.

EV2G in NSW: arbitrage-only is more profitable than frequency control in the other two geographies

Using the same methodology as in PJM, scenarios are established by taking the identical EV numbers per household, as is shown by Table 5.6. With these number of EV, no supply shortage was observed.

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

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

Figure 5.22 presents the results of three scenarios in NSW's real-time energy market. Similar to the situations in ESS cases, the market potential of arbitrage is higher than the other two geographies due to the price volatility as is cussed previously. The potential profit obtained in the scenario of "EV Number 2016" was 198 USD/(a · MW), which was 66 and 9 times the numbers in corresponding cases in Germany and PJM respectively. It is even higher than profits from business cases where frequency control are involved in other two geographies. Since arbitrage using EV is much more feasible in technology, such a high arbitrage profitability shall provide more incentives for the market participates and makes the business appealing if the number of EV will indeed grow in line with our scenarios.

Finally, it shall be noted that even in the scenario with 2% EV market share, the market potential of arbitrage via EV2G was found to be 4105 USD/(a · MW), which was just 3.8% of the overall arbitrage potential using ample size of generic ESSs as was shown by Figure 5.14, leaving a vast space for other technologies.

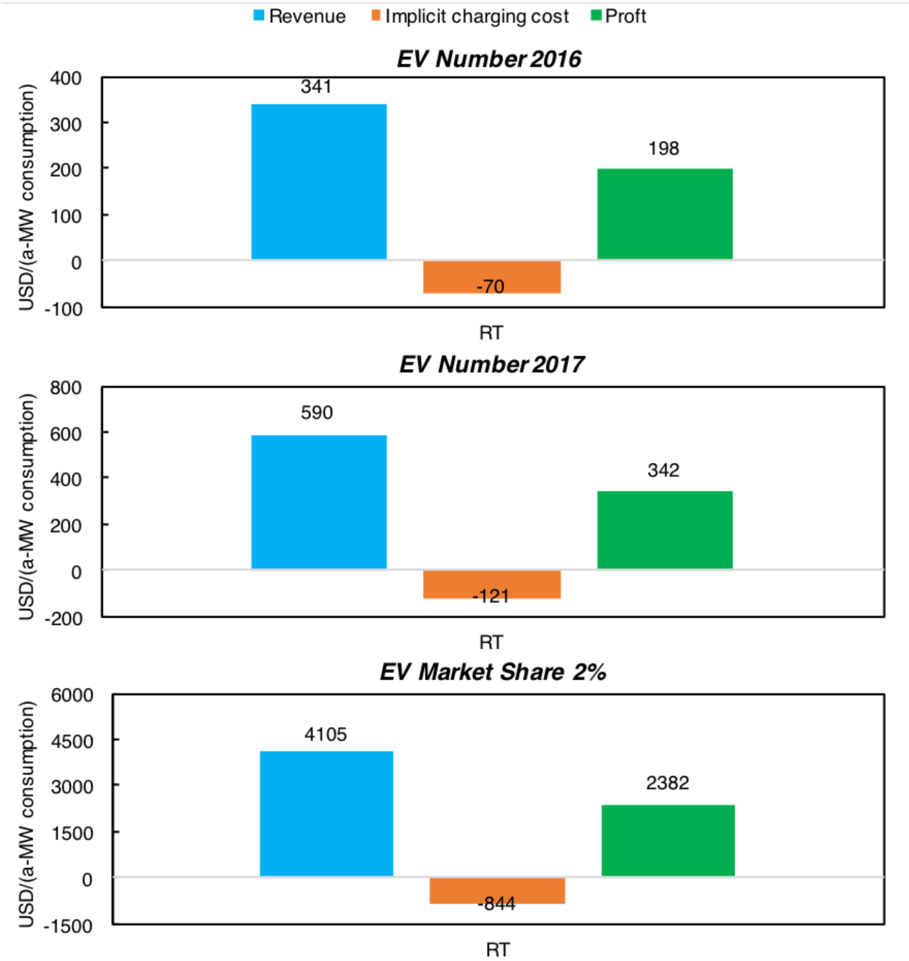

Figure 5.22: Market size and profitability of EV2G in NSW Electricity markets

Summary

The key indicators for the market size and profitability, in both normalized and absolute values are summarized in Table 5.7-5.9. Values were extracted at different scenarios where they are maximized. Therefore, the maximum revenue and maximum profit may not be obtained at the same time, especially for ESSs, as has been discussed at the beginning of this section.

Table 5.7: Summary of market size and profitability of flexibility management in Germany

Item[a]	**Arbitrage**	**Balancing**		**Multitasking**
	DA+ID	BE	FCR[b]	DA+ID+FCR
Energy Storage System				
Max. Revenue [USD/(a · MW)]	6426	3872	2012	10 247
Max. Profit [USD/(a · MW)]	-	17	-	-
Max. Revenue [mUSD/a]	380	229	119	606
Max. Profit [mUSD/a]	-	1	-	-
Max. Profitability Ratio	(-92%)	7%	(-40%)	(-60%)
Cost break-even[c]	(-84%)	-	-	-
Electric Vehicle to Grid				
Max. Revenue [USD/(a · MW)]	1961	-	-	3224
Max. Profit [USD/(a · MW)]	8	-	-	1986
Max. Revenue [mUSD/a]	116	-		190
Max. Profit [mUSD/a]	0.5	-	-	117
Max. Profit per EV [USD/(a)]	4	-	-	731

[a]Maximum values of items are obtained in different scenarios
[b]Frequency control reserve, including both PCR and SCR
[c]Cost reduction ratio

Table 5.8: Summary of market size and profitability of flexibility management in PJM

Item[a]	**Arbitrage**	**Balancing**		**Multitasking**
	DA+RT	RegD	RegA	DA+RT+Reg[b]
Energy Storage System				
Max. Revenue [USD/(a · MW)]	6333	524	467	7324
Max. Profit [USD/(a · MW)]	0	11	0	53
Max. Revenue [mUSD/a]	556	46	41	643
Max. Profit [mUSD/a]	0	1	0	3
Max. Profitability Ratio	(-88%)	8%	(-29%)	9%
Cost break-even[c]	(-81%)	-	-	-
Electric Vehicle to Grid				
Max. Revenue [USD/(a · MW)]	1504	-	-	2351
Max. Profit [USD/(a · MW)]	261	-	-	1218
Max. Revenue [mUSD/a]	132	-	-	206
Max. Profit [mUSD/a]	23	-	-	107
Max. Profit per EV [USD/(a)]	45	-	-	1657

[a]Maximum values of items are obtained in different scenarios
[b]Including both RegD and RegA
[c]Cost reduction ratio

Table 5.9: Summary of market size and profitability of flexibility management in NSW

Item[a]	**Arbitrage** DA+RT	**Balancing** FCAS[b]
Energy Storage System		
Max. Revenue [USD/(a · MW)]	109 301	2933
Max. Profit [USD/(a · MW)]	-	-
Max. Revenue [mUSD/a]	872	23
Max. Profit [mUSD/a]	-	-
Max. Profitability Ratio	(-70%)	-
Cost break-even[c]	(-68%)	
Energy Storage System		
Max. Revenue [USD/(a · MW)]	4105	-
Max. Profit [USD/(a · MW)]	2382	-
Max. Revenue [mUSD/a]	33	-
Max. Profit [mUSD/a]	19	-
Max. Profit per EV [mUSD/a]	326	-

[a] Maximum values of items are obtained in different scenarios
[b] Values based on payment on a whole system level without involving technical analysis
[c] Cost reduction ratio

5.2.3 Impact analysis of renewable penetration

As is mentioned at the beginning of this section, understanding the impact of some key factors is crucially viable to plan future business on flexibility management, as the market may evolve rapidly. Among all the factors, we have selected the renewable penetration as the most influencing factor and studied in this thesis. The rationale can be explained as the renewable penetration would change most radically compared to other factors and is viewed as the essential driver of growing needs for flexibility, which has been elaborated in Chapter 1.

Growing capacity of renewable generations will influence both wholesale energy and frequency control markets as we have seen from the literature; refer to Chapter 2. However, determining the requirement for frequency control reserve is an extremely sophisticate process of grid planning, which is rarely addressed by academic articles. Grid planner may initiated large-scale research project dealing with this problem. Referring to a study ordered by PJM and conducted by a research consortium led by GE Consulting [21], an average of 1533 MW frequency regulation reserve would be required in a scenario where the 14% RPS (Renewable Portfolio Standard by each state in PJM region) is to be met by 2026. This is about 2.2 times of the amount in 2016 (700MW). Assuming the price stays at the same level, one may multiply the ratio of 2.2 to the valuation results presented in preceding section, in order to make a rough estimation of the future. Nonetheless, the penetration of renewable will not only influence the frequency control market physically but also institutionally where the design of market may be revised. Therefore, understanding quantitatively the impacts of renewables on both volume and price in frequency control market are significantly beyond the scope of this study.

In this thesis, we would only focus on the wholesale energy market. Day-head markets in both Germany and PJM are taken for case studies.

In order to simulate price scenarios with different level of renewable generation, we adopted a simplified method by multiplying the time-series data of actual renewable generation in 2016 by a certain ratio. No simulations with wealth data were involved.

In Germany, the installed capacity of solar and wind has already accounted for a significant share, i.e. 83.85 GW as 41.7% of the total generation capacity. Therefore, we made conservative scenarios where the assumed capacity of wind and solar are 85% to 115% of present level with a step length of 5% of the existing capacity, equal to 4.19 GW per step.

For PJM, the installed capacity of wind and solar was merely 6533 MW in 2016, which is 3.7% of the total capacity. The 14% RPS, as is mentioned above, requires PJM to install a total of 40 190 MW solar and wind generations by 2026. Compared to the number in 2016, this indicates a compound annual growth rate (CAGR) of 20%. Therefore, we created additional scenarios beyond the ones that are consistent with German cases (85-115%) as 5-year forecasts the 20% CAGR.

Model setup and validation

In order to analyze the future trend of market value by understanding potential impacts of certain key factors, the market simulation module was designed as is introduced in Section 4.2.2. In this section, we would demonstrate the setup and validation of the module based on day-ahead market and generation data in Germany in 2016.

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

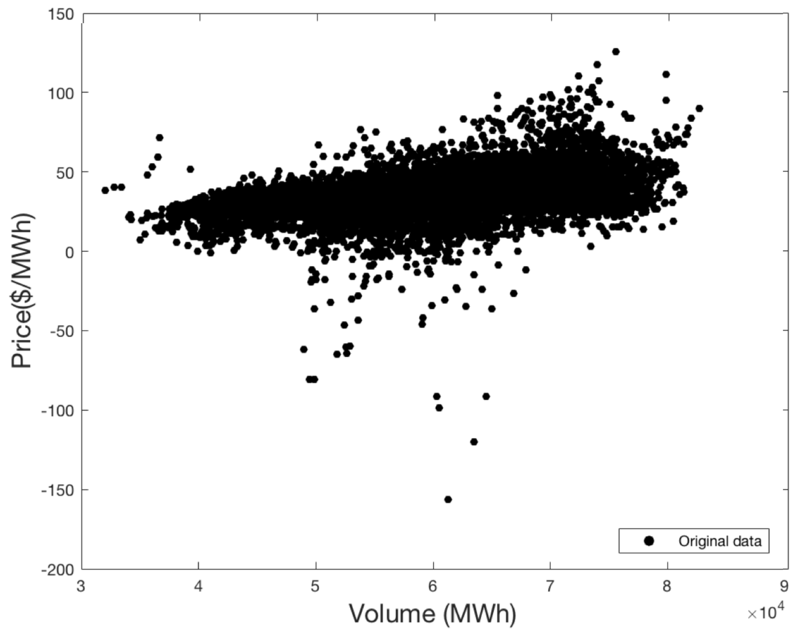

Figure 5.23: Germany day-ahead price-volume data in 2016

The pattern of merit-order effect is not clearly recognizable from the original data mainly due to the disturbs of variable renewable generation which has raised significantly in past years. This prevents us from directly applying merit-order models developed by previous studies [145] [98]. Therefore, we applied the algorithm described in Section 4.2.2 which take into account the renewable generation and bounded flexibility of conventional generations. Figure 5.24 shows the transformed pattern of data where a clearer merit-effect is identifiable. Figure 5.25 projects the classification to the original data distribution and it can be seen that the algorithm has successfully separated the data points where the price was driven to be higher or lower than average level due to the uplift effects introduced in 4.2.2.

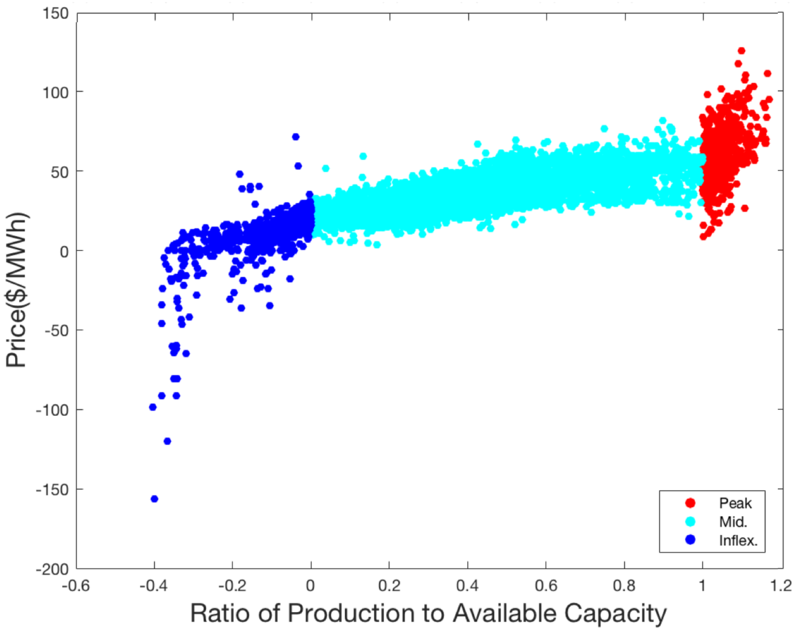

Figure 5.24: Transformed pattern of Germany day-ahead price-volume data in 2016

Thereafter, we fitted the transformed data pattern with the piece-wise function defined by (4.19). The estimated parameters are listed in Table 5.10. It shall be noticed there are price limits applied in EPEX day-ahead market [146] which is between -500 to 3000 EUR/MWh, equal to -600 to 3.6 USD/MWh using the specified currency exchange rate. The fitted merit-order curve is illustrated by Figure 5.26 and distribution of errors between the fitted price and actual price is shown by Figure 5.27.

Table 5.10: Parameters of the merit-order model in Germany

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

We simulated the day-ahead price using this merit-order model and compared to the actual market data. It can seen from Figure 5.26-5.27 that while the fitted merit-order price shows a good fitness to the actual price in

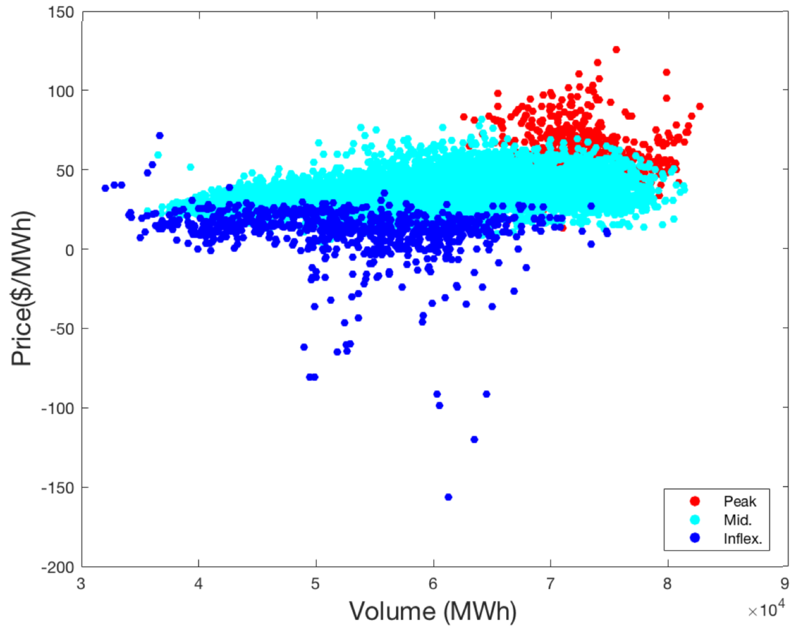

Figure 5.25: Classification of Germany day-ahead price-volume data in 2016

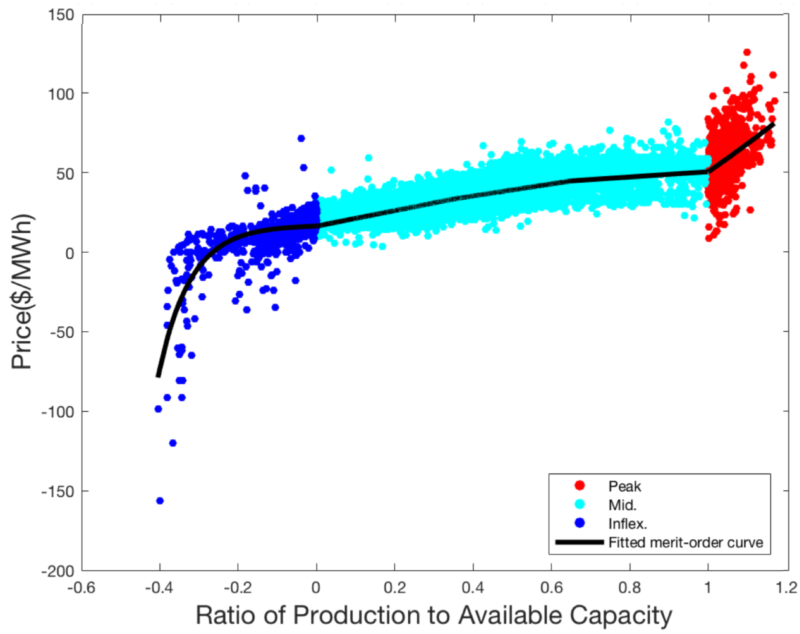

Figure 5.26: Fitted merit-order curve with Germany day-ahead price-volume data in 2016

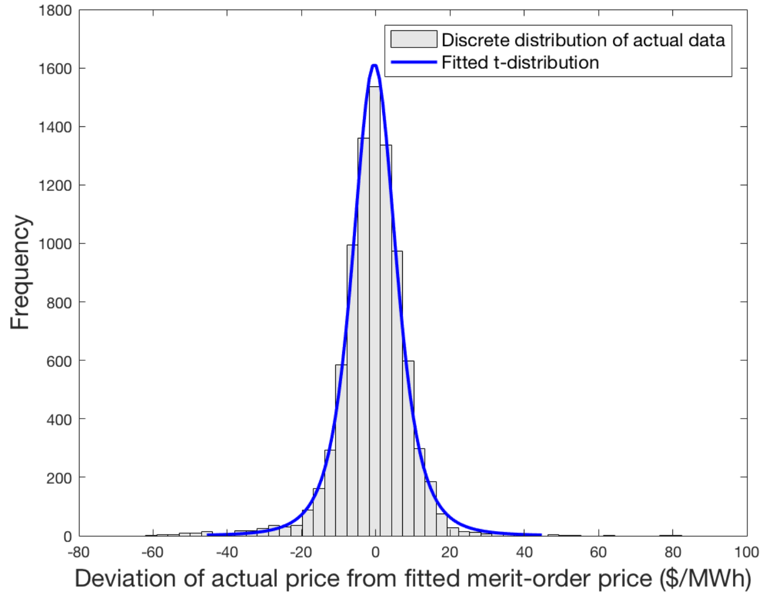

Figure 5.27: Distribution of errors between fitted merit-order price and actual price

terms of general trend, the stochastic movements of the price are eliminated. Merely with the merit-order model, a smoothed curve of price time-series would be generated where the drastic jumps of price cannot be captured, as is demonstrated by Figure 5.28.

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

Table 5.11: Parameters of the stochastic price movement of SARMA models in Germany

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

Therefore, a seasonal auto-regressed moving-average (SARMA) model as is described in 4.2.2 is applied to simulate the stochastic components of the price. The estimated parameters of the SARMA model based on

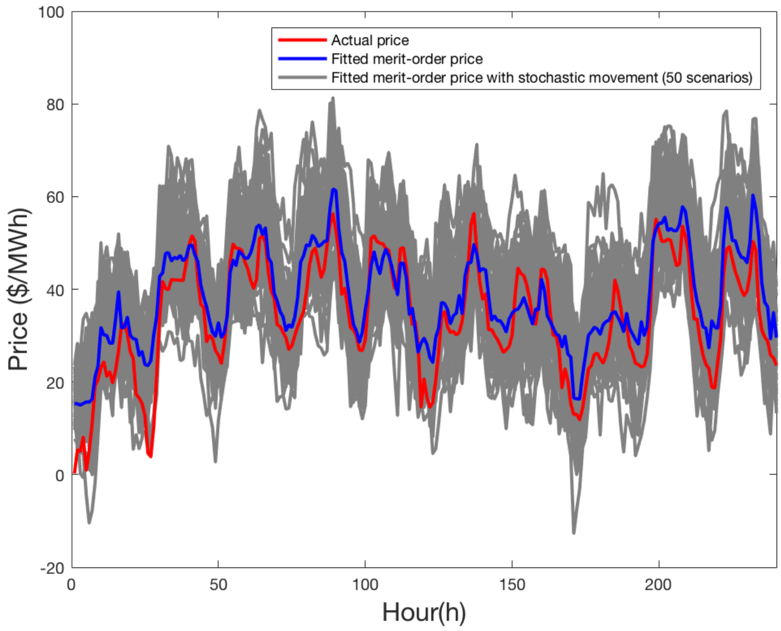

Figure 5.28: Generated price scenarios

the error signal characterized by5.27 is listed in Table 5.11. Thereafter, we conducted Monte-Carlo simulations and generated 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 5.28. Using these generated price profiles, we calculated the revenue for 100 scenarios and compare the average and median value to the result obtained with actual price signal, which shew perfect fitness in Figure 5.29. There are no significant differences between the average and median value observed, but for robustness and avoiding effects of outliers, we would use the median value as the simulated result for experiments in proceeding sections.

We applied the same procedure to develop the model for PJM. It was noticed that the situation when the residual load is in the range of inflexible generation is rarely observed in PJM, which can be explained by the relative low installed capacity of renewable generations. Therefore, we migrated part of the merit-order model for inflexible generation based on Germany's data here, which shall however have insignificant effects because the lowest price is bounded at 0. Negative pricing is not explicitly an issue in PJM's market so far although PJM is fully aware of this issue but waiting for FERC's initiative to address the potential negative price formation [147]. Without unambiguous rules, we would not allow negative prices in our modeling. The highest price, on the other hand in PJM is capped at 1000 USD/MWh [148].

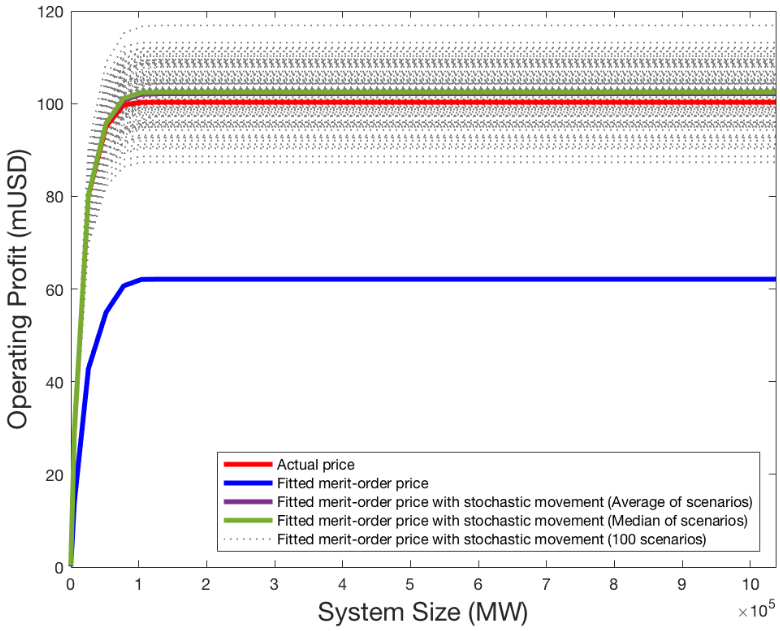

Figure 5.29: The revenue with different price scenarios for model validation in Germany

The parameters for the merit-order model in PJM are listed in Table 5.12. The SARMA parameters are presented in Table 5.13.

Table 5.12: Parameters of the merit-order model in PJM

Class	**Parameters**		
	a	b	c
Inflex.	17.05	-1.49	-12.35
	23.50	16.40	
Mid.	32.02	13.41	
	3.58	31.90	
Peak	10.70	501.35	-5.32

Table 5.13: Parameters of the stochastic price movement of SARMA models in PJM

SARMA parameters	
$\phi_1 = 0.690$	$\theta_1 = 0.107$
$\phi_2 = 0.125$	$\theta_{24} = -0.003$
$\phi_{24} = 0.298$	$\theta_{168} = -0.399$
$\phi_{168} = 0.560$	

Renewable penetration in Germany: at the inflection point

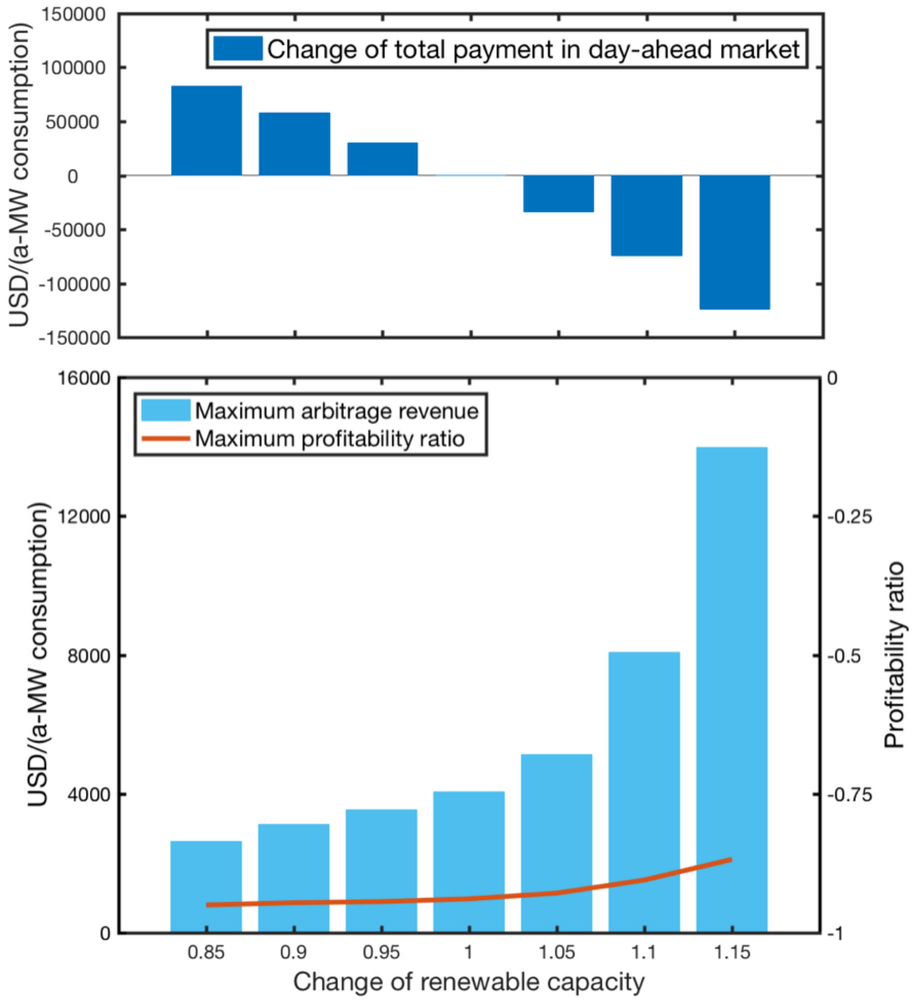

Figure 5.30: Impacts of renewable generations on revenue and profitability of arbitrage using flexibility as well as on total amount of transations in day-ahead market in Germany

The results are illustrated in Figure 5.30. We can see while the revenue potential of arbitrage using flexibility grew insignificantly with renewable capacity growing from 85% to the present level, it would accelerate rapidly afterwards. The potential revenue would almost double its value with 10% additional renewable generation and triple with 15% renewable growth. This indicates the day-ahead market in Germany is at a inflection point where the volatility will increase drastically with more renewable making it more favorable for arbitrage. Quantitatively, it was found when renewable capacity grew from 85% to the present level, the addition of each 5% growth would lead to a increase of 12-23% on the the standard deviation of day-ahead price. In contrast, the rises of volatility would be 74-225% for each additional 5% growth of renewable growth from present level to 115%.

However, it is known that the renewable penetration will not only increase the price volatility but also lower the average level of price via the so-called merit-order effect. In our study, the merit-order effect was found to be 0.75 - 1.12 USD/MWh per additional GW of renewable generation, which accords with the number found by previous research where the merit-order effect was accounted to be 0.8-2.3 EUR/MWh per additional GW in Germany by statistic studying on the real data between 2008 to 2012.

Without any interventions, this effect would soon make the price unacceptably low to generators. In the scenario with 15% more renewable the average price in day-ahead energy market will reduce by 14 USD/MWh which would almost half the revenues received by generators as a whole. The growth of arbitrage revenue would be one order of magnitude smaller than the reduction of overall amount of payment to generators. It was certain that players will take actions against this trend. The policy supports on renewables may also be gradually abated as what have already been noticed from the real world and introduced in Section 5.1.

Market players with conventional generations that are suffering the pressure of decreasing price due to renewables may embrace flexibility in order to mitigate the conflicts of renewables and inflexible generations or even enhance their market power to strategically maintain the price level as is studied in [78]. The effects of arbitrage using flexibility on wholesale energy market would be briefly discussed in Section 5.2.4 on a schematic level.

Nevertheless, BESS might not be the right choice to achieve these goals. As the profitability ratios of the pre-defined BESS in our study were still deeply negative and raised insignificantly to be optimally -87% from nowadays's level of -94%.

Renewable penetration in PJM: arbitrage potential bounded by non-negative pricing

Similar work was conducted in PJM's day-ahead market. Results are shown by Figure 5.31. With trivial addition of renewable generations from 85-115%, the potential arbitrage revenue would increase slightly by about 0.7-1% for each 5% increment. However, further growth of renewables will lead to a decreasing trend of arbitrage potential. This could be explained because of the non-negative price. Without compensation from negative prices, the arbitrage value dropped along with the shrink of average electricity price due to merit-order effects. The merit-order effect here was found to be 1.05 - 1.13 USD/MWh per additional GW of renewable capacity.

PJM reported that it had received negative offers from wind generation enabled by the federal wind production tax credit (PTC) [147]. However,

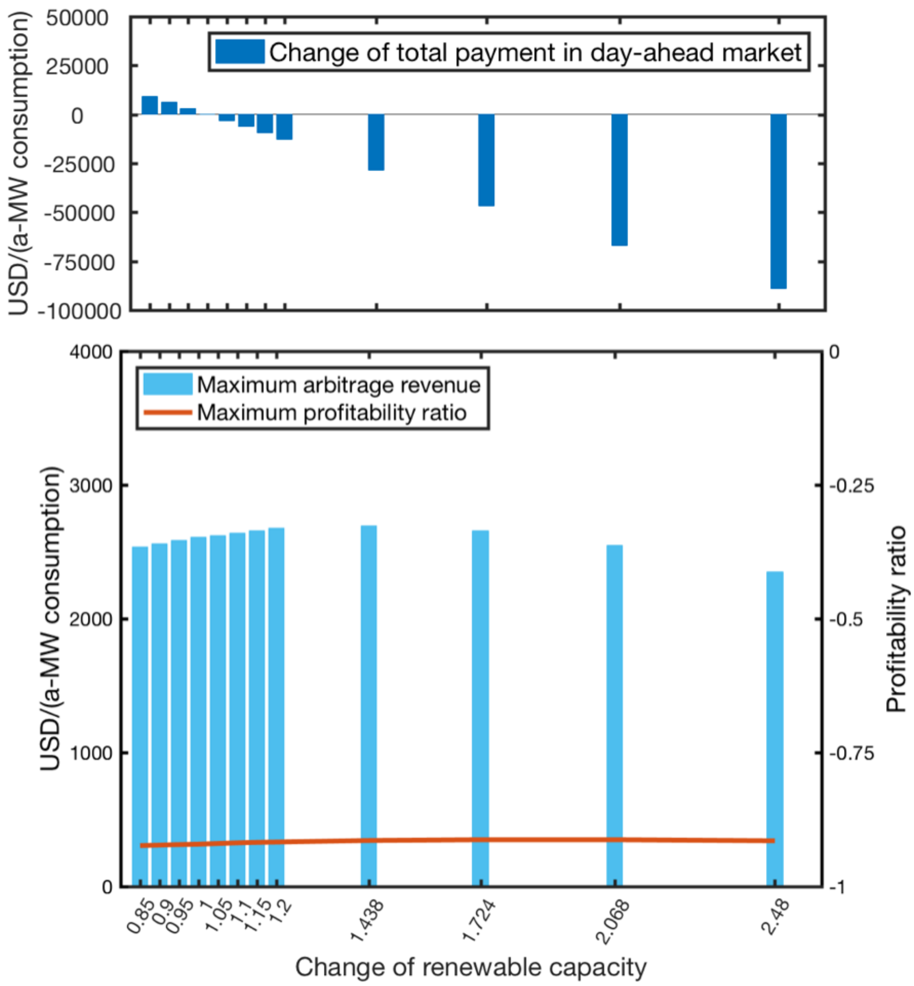

Figure 5.31: Impacts of renewable generations on revenue and profitability of arbitrage using flexibility as well as on total amount of transations in day-ahead market in PJM

without a clear framework of negative price formation, predictive studies would hardly be robust.

5.2.4 Sensitivity analysis

Throughout the whole study, there are two crucial assumption made, i.e. the perfect predictability assumption and fixed price assumption. Elaborated in the literature, this two assumptions are common pragmatic ways in similar studies to indicate a idealistic value as upper bound. Nonetheless, it is necessary to study how reliable the results are based on these assumptions. Besides, the sensitivities of other parameters that were determined based on assumptions are also tested in this section.

Limited predictability

Validity and issues regarding this assumption was elaborated in Section 2.2.2 in the literature review. In reality, players have a set of methods to forecast the price in short run, some of which are quite efficient and accurate [99] so close to the perfect forecast assumption. However, while valuing the total market, we shall view the market as whole where players' ability of predicting vary significantly. Therefore, here we would calculate the maximum deviations from our previous estimations in a worst case scenario, i.e. derive lower bounds, where players' forecasting ability is poor. This worst forecast method is defined as "backcast" as is explained in Section 2.2.2, via which market participates directly take the historical price to foresee the future price. This is the simplest way of forecasting the price and is feasible for all players without the needs for any modeling abilities, so shall indeed represent the lowest possible values.

We tested two scenarios where the price is lagged by 1 day and 1 week respectively, i.e. taking the day-ahead and week-ahead price as the predicted price. The results are summarized in Table 5.14 to 5.16.

Table 5.14: Summary of sensitivity analysis on predictability in Germany

Case	**Backcast - 1 week**		**Backcast - 1 day**	
	MR[a]	MPR[b]	MR[a]	MPR[b]
ESS				
DA	-50.6%	-2.3%	-48.9%	-2.1%
ID	-50.0%	- 3.2%	-52.5%	-4.1%
BE	-133.1%	- 131.8%	-101.3%	-112.2%
PCR	-0.0%	- 0.0%	N.A.[c]	N.A.[c]
SCR	-10.3%	- 0.6%	N.A.[c]	N.A.[c]
DA+ID	-52.3%	- 4.1%	-52.1%	-4.7%
DA+ID+SCR	-35.9%	- 0.9%	-38.6%	-1.3%
DA+ID+PCR+SCR	-33.3%	- 0.0%	-33.0%	-0.1%
EV2G				
DA	-36.1%	-1.2%	-58.6%	-1.8%
DA+ID	-41.5%	-2.3%	-59.0%	-3.0%
DA+ID+SCR	-22.3%	-1.1%	-30.4%	-1.6%
DA+ID+PCR+SCR	-11.6%	-1.1%	-22.0%	-1.5%

[a]Max. Revenue: difference in percentage
[b]Max. Profitability Ratio: difference in percentage point
[c]Primary and secondary control markets are organized by weekly auctions

First of all, it can be noticed the results for providing balancing energy dropped considerably, which verified our previous analysis that this market is not practically feasible for market players due to the volatility and unpredictability of balancing energy price, reBAP.

Besides, we can see the cases involving arbitrage is more sensitive than cases with frequency control services. This implies that predicting price precisely for selling frequency control reserves is not as a critical issue as for arbitrage.

Finally, it was found while backcast for 1 day had sightly better performance than backcast for 1 week for ESS, the situation reversed for EV2G. This can be explained because EV driving behaviors embedded in our model also have a weekly pattern, as was shown in preceding section. It is necessary to matching EV driving profiles well with the price profiles.

Table 5.15: Summary of sensitivity analysis on predictability in PJM

Case	**Backcast - 1 week**		**Backcast - 1 day**	
	MR[a]	MPR[b]	MR[a]	MPR[b]
ESS				
DA	-35.5%	-1.9%	-17.9%	-1.1%
RegD	-4.4%	-6.4%	-4.4%	-5.1%
RegA	-33.3%	-22.4%	-26.7%	-19.3%
DA+RT	-51.6%	- 7.2%	-39.5%	-6.1%
DA+RT+RegD	-47.8%	-5.4%	- 36.7%	-4.5%
DA+RT+RegA	-48.6%	- 12.9%	-37.2%	-11.2%
DA+RT+RegD+RegA	-48.4%	- 10.3%	-34.7%	-8.7%
EV2G				
DA	-32.9%	-0.9%	-18.3%	-0.6%
DA+RT	-50.3%	-3.2%	-43.8%	-1.0%
DA+RT+RegD	-39.5%	-2.5%	-34.8%	-2.3%
DA+RT+RegA	-41.9%	-4.1%	-36.4%	-3.5%
DA+RT+RegD+RegA	-34.4%	-4.1%	-29.9%	-3.5%

[a]Max. Revenue: difference in percentage
[b]Max. Profitability Ratio: difference in percentage point

Compared to results in Germany, the sensitivity of predictability shows a similar pattern. The revenue reduction is less significant in PJM's day-ahead market compared to Germany, implying a more stable price profile. This can be explained that a power pool with capacity obligation can maximize the participation of all resources and suppress virtual transactions, thereby leading to a robuster price formation than a power exchange. Revenue potential from RegD altered sightly while the value from RegA significantly dropped. This is because in the original plans players were assigned with perfect predictability of frequency control signal as well so that they were able to better tackle the non-energy-neutral signal. In reality, frequency control signals are impossible to forecast. Therefore, the merit of energy-neutral signal is again demonstrated. However, it shall be emphasized again that implementing energy-neutral signals is a complex and challenging task. A energy-neutral signal might be most beneficial to the system, since it might move to the same direction as the error in order to maintain energy neutrality. This is the rationale why PJM re-engineered the RegD to be conditional energy neutral.

Table 5.16: Summary of sensitivity analysis on predictability in NSW

Case	**Backcast - 1 week**		**Backcast - 1 day**	
	MR[a]	MPR[b]	MR[a]	MPR[b]
ESS				
RT	-58.8%	-16.6%	-47.6%	-14.7%
EV2G				
RT	-56.4%	-13.8%	-51.3%	-12.7%

[a]Max. Revenue: difference in percentage
[b]Max. Profitability Ratio: difference in percentage point

In NSW, although we have pointed out the higher volatility in its real-time markets leads to a higher potential of arbitrage compared to markets in Germany and PJM, it also demands higher precision of price forecasting. The revenue and profitability dropped more sensitively than arbitrage cases in the other two geographies.

Responsive price

While the amount of flexibility reaches a significant level, their trading behaviors will certainly disturb the market and affect the price. Especially in the case of arbitrage where the price volatility is being utilized for value creation, the actual revenue would be more sensitively depending on the responsive price effect. Regarding frequency control market, the revenue relies on the average price level rather than the price volatility and the distinct price formation mechanism such as the pay-as-bid mode in German markets shall suppress significant disturbances of new players on market price.

Therefore, we studied the effect only on wholesale energy markets here. It shall be firstly pointed out, with a responsive price, there are still two distinct scenarios exist, i.e. price taker and price marker. In the price taker scenario, although the players' actions will affect the price formation, the market is highly competitive so each player has negligible market power. In contrast, price maker may exist in some markets where the competitions are sufficient and few players can strategically exert its market power to distort the market price. Among these two cases, it is clear that the price taker scenario would indicate a lower bound while price makers are more likely to receive higher payments or better fulfill their strategic goals. Therefore, in this section, we take the worst case scenario where players have no market power. It shall be noticed that in this scenario, their price forecast is not imperfect since the price formation takes place after their decisions are made.

The results for the day-ahead market in Germany as an illustrating example is shown by Table

(To be continued)

Sensitivity analysis of other parameters

Chapter 6

Conclusions and outlook

Appendix A

Accounting rules and electricity market data prepration

Appendix B

Other

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