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Valuation of Energy Flexibility Solutions in Different 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].

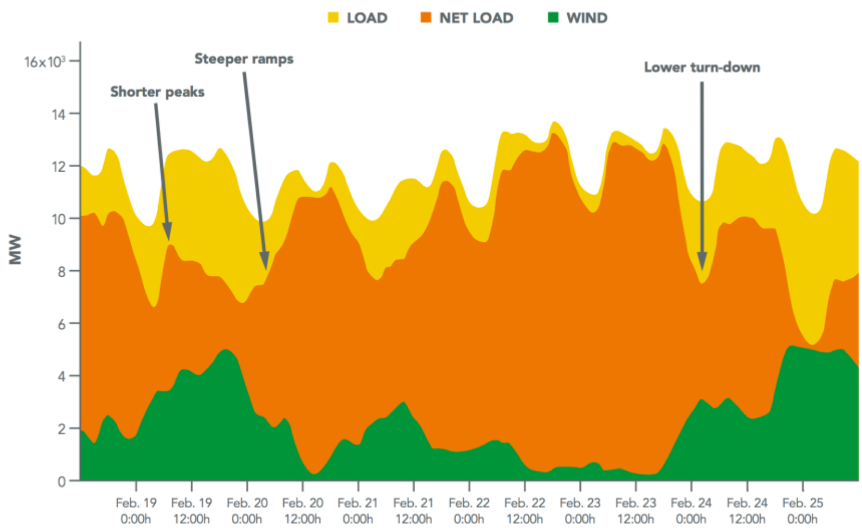

Figure 1.1: An illustrative example of net load profile [1]

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.

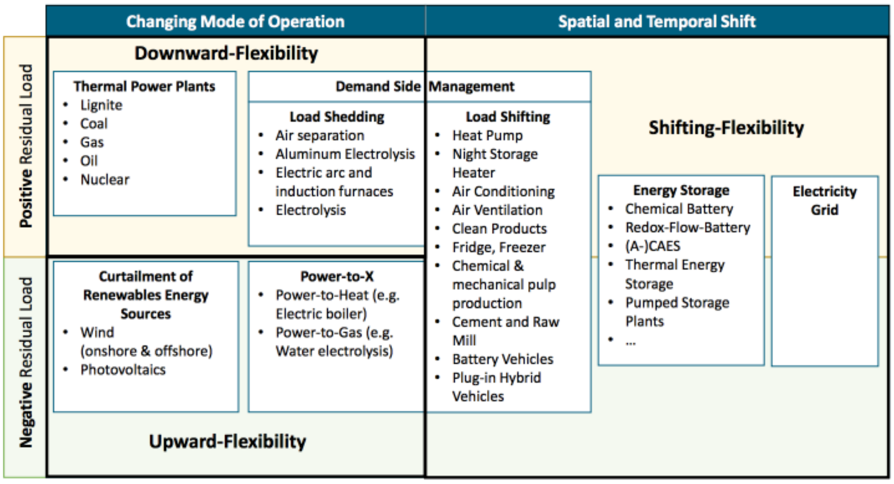

Figure 1.2: Catalog of flexibility solutions [9]

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

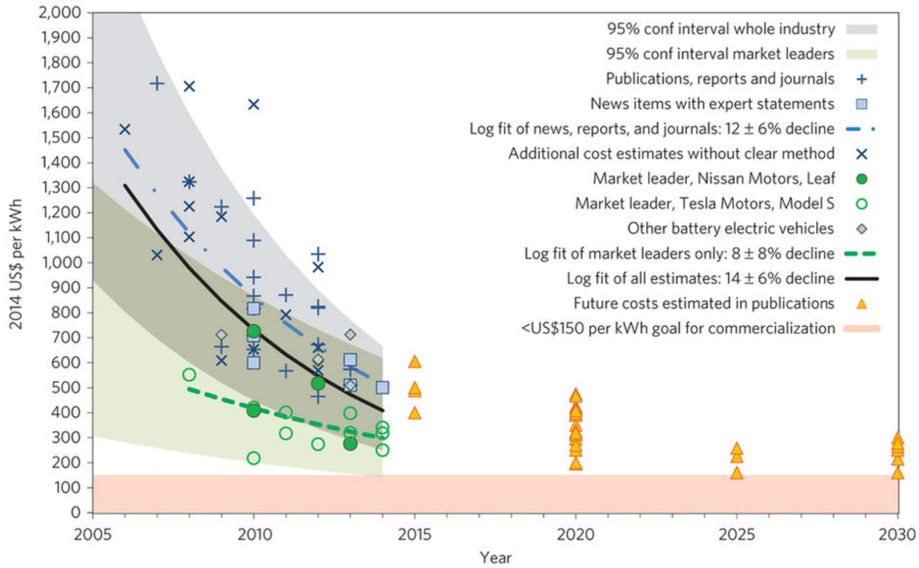

Figure 1.3: Cost of Li-ion batteries for electric vehicles [42].

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].

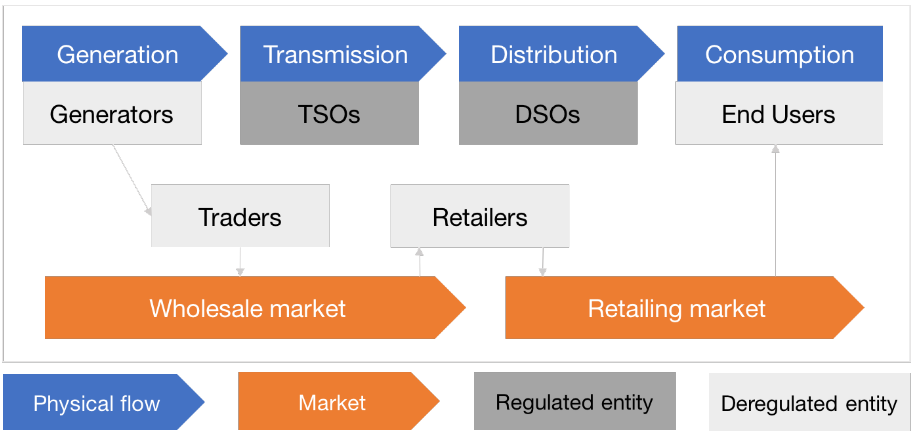

Figure 1.4: Schematic illustration of the liberalized power market

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 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 adequacy 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) and distribution system operators (DSOs) 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 adequacy	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 (i.e. market size and profitability) of flexibility
  - in different markets?
  - using different technologies?
- How will the 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 assessment. Analytical frameworks are established for qualitative assessment and a techno-economic model is established for quantitative valuation. 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 solutions, with a special focus on the quantitative valuation methodologies.
- **Chapter 3** studies the power market structures and how they impact on the value creation of flexibility solutions in a generic way. An analytical framework for qualitatively analyzing the opportunities of flexibility solutions based on a comparative view on different power market regimes.
- **Chapter 4** introduces the methodology how the techno-economic model is established to make quantitative estimations.
- **Chapter 5** presents the results of 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 The Market for Flexibility Management: A Literature Review

This chapter reviews the existing literature on methodologies that are related to quantifying the market for flexibility management. It was found that our questions are not perfectly answered since existing research was geared to different stakeholders and perspectives. However, researchers have developed a number of validated methodologies which are of significant reference value for this study. We have mapped these studies and selected the ones we consider to be both effective and computationally tractable.

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 often targeted at different audiences. We categorize the selected works into two groups with distinct perspectives, i.e. micro- and macro-system 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 the context of a specific business or project.

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. There are reports that exclusively focus on 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 project specifics. The associated complexity does not always add additional value to our more general 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 results are proof-of-concept for a methodology so cannot be used as direct inputs for our analysis. Besides, these models often 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 that some market constraints such as liquidity can be ignored.

Macro-perspective

Another perspective is taken by publications made for the interests of policymakers, market designers and grid planners. These studies stand on a macro-perspective and investigate the benefits or requirements of flexibility for power systems. They primarily pursue 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 usually investigations on deferred infrastructure expenses [41,71,72], which are not within the core scope of this study.

The results derived from these 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 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 there is seldom symmetry 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 markets organized by independent system operators (ISOs) 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 to 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 of the entities [69]. However, for each group of stakeholders, it is helpful to understand the rationale 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 they can make better decisions. On the other hand, policymakers shall consider the needs of market participants so that they can better encourage their participation by well-designed incentives.

As a consequence, there are researchers who 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 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 remunerate owners. Thereby, the optimization is to estimate the maximum possible value obtained by players with a defined strategy and subject to constraints from markets and technologies.

In terms of detailed implementation, these models can be classified into different approaches. Beyond briefly introducing these approaches, we 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 participant to manipulate the price of an item to raise its own financial or strategic benefit. 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 attention from researchers and many methodologies have been developed based on multi-optimization equilibrium modeling or making price a function of decisions. However, due to computational complexity, these methodologies are seldom used for valuation in 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 participants 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 impact 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 such as the portfolio of each simulated entity. Therefore, it is more often that studies are based on a 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 a fixed input to the single-optimization model. In this way, the decision making entity is a price taker as its decision will not affect the price.

An alternative way to internalize the price formation is to make the price a function of decision variables rather than being constant. However, such a method will make the optimization non-linear since the objective function is often the product of price and decision variables. The function has to retain some simplicity to be tractable. 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 turn to the equilibrium model as introduced earlier to study situations with price makers.

Overall, although there is an abundance of literature studying price makers with flexibility, these methods are seldom applied for estimating real market values, which is however of most interest to us. Therefore, a pragmatic approach is to assume all participants 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 dominant 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, while perfect competitive market may be an exorbitant assumption, results based upon it do provide a decent benchmark reference.

2.2.2 Predicting the price

With the approach of single-optimization modeling using exogenous clearing, price is a crucial input to the optimization problem. It is of great importance how the value 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 assumptions 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 eliminates the uncertainty of price together with associated risks. Therefore, many studies developed auxiliary simulation models to generate price scenarios in complement 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 is more commonly implemented by academic studies, as is mentioned, is 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]. The SARIMA model is of order $(p, d, q) \times (P, D, Q)_s$. 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 SARIMA $(2, 0, 2) \times (2, 0, 1)_s$ with seasonal part being AR (24,168) and MA (168)[1] in this study where the profits of EV aggregators were assessed. Similarly,

[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.

Mahmoudi *et al.* [101] implemented a SARIMA $(6,1,3) \times (1,0,0)_s$ 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 changing 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 to understand the impact of possible changes of market conditions (increased RES penetration). For the price simulation model, the merit-order model and stochastic SARIMA model are synthesized, which will be discussed in detail in Chapter 4.

It should be noted that among all the studies mentioned above, only one article [102] simulated the price for frequency control services in the short run using SARIMA model, while the others are exclusively for simulation of energy price. There is no literature found for long-term price trend of frequency control services. This can be explained by many reasons but most importantly it should be because the mechanism of price formation, the responsible party for procuring, as well as design specifications of frequency control services vary significantly among different market regimes and may change over time[3]. There are some works made on a macro-perspective to provide references for market designers and grid planner to anticipate future demand of frequency control services and propose improvements on frequency control market design [21, 103]. Nevertheless, the evolution of price level that is of more concern on a micro-perspective, was not discussed in the literature. Considering these limitations, we will only carry out quantitatively valuation for long-term scenarios for energy arbitrage, while for frequency control services we will quantify their market values under current market conditions together with some qualitative analysis.

Perfect foresight vs. limited predictability

When 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 of flexibility compared to what can be captured in reality [69].

Stochastic price simulation, as introduced previously, is certainly a powerful way to resolve the issue. However, the stochastic approach adds complexity and requires more computation time, so deterministic 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

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

[3]More details and examples can be found in Section 3.3

using back-casting techniques, i.e. determine the future dispatch plan with historical data [57, 104, 105]. 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.

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 type of services at the same time. These operating models may increase the profitability given the 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 [74,105], increasing studies were carried out recently from the perspective of aggregators. Han *et al.* [106] studied the optimal trading strategy of a VPP operator with distributed generations (wind power), energy storage and flexible load (load shifting). Calvillo *et al.* [107] 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.* [108] 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.* [107] studied the optimal planning by referring to methodology developed for microgrid (MG) operators [109]. 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 a task of the grid planner, so it is not considered. Instead, we 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, 110], 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 multitasking are observed in studies on energy storage [59, 62, 110], EV2G [102, 111–113] and DR [114].

Multitasking is performed and tested in our study.

2.2.4 Formulating the problem

Deterministic modeling vs. stochastic modeling

In our study, 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 these terms are involved. Strictly, the objective function of an optimization with a stochastic approach is maximizing the expectation of value over different scenario and formulated as: [69]:

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

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.* [115] and Xi *et al.* [116] are formulated in this way. It is worthwhile to mention that in the paper by Qin *et al.* [115], 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 deterministic 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, 106–108, 117]. More specifically, Zhang *et al.* [85] considered the uncertain outputs of DG. Mahmoudi *et al.* [101] use a random Boolean indicator to represent the participation of DR customers. Xu *et al.* [108] 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, 106].

Nonetheless, stochastic approach is not a must [69]. Using the deterministic 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 [107]. The most important outcome obtained with stochastic approach in addition to results using deterministic approach is risk control.

In our study, we apply the deterministic approach 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 computational 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 seek measures such as the primal-dual approach to convert the non-linear programming to be mixed integer linear programming [55, 85, 87, 118] or to approximate the non-linear objective function using a piece-wise linear function [101].

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

2.3 Summary

Chapter 3

Power Markets and The Role of Flexibility Management: An Analytical Framework

This chapter aims at offering a comparative view on different power market regimes, based on which an analytical framework can be established. Such a framework offers technology vendors a solid foundation for qualitatively analyzing the opportunities of flexibility management in a given market context. By mapping a list of mature power markets worldwide, we extract some key attributes of power market structures that impact the value of flexibility management.

3.1 Motivation for a power market analysis framework

Conceived in the 1980s and facilitated in the 1990s, liberalization of power markets has become the mainstream worldwide [17, 18, 51]. However, different conditions exist across economies including historical, political and climatic factors. As a result, structures of these power markets tend to be very heterogeneous. This brings great challenges to companies that pursue a cross-regional or even global footprint, since business models for flexibility management as well as their feasibility and performance depend extensively on the power market structure. Compared to other stakeholders that are interested in flexibility management such as utilities and regulators, technology vendors are more likely to have international ambitions. This is not only because they have fewer regulatory barriers, but also because firms with higher research and development (R&D) intensity have stronger motivation for expanding geographic boundaries to mitigate market risks and seek growth opportunities [119].

Therefore, in this chapter we map the taxonomy of power markets with a particular focus on characteristics related to flexibility management, in order to provide a general framework for technology vendors facing different power markets.

Such a global view is established by generalizing and comparing market regimes in different systems that are listed in Table 3.1. We will name a few of them as typical examples while discussing each structural attribute. However, it shall be noted that the goal of this chapter is not to provide comprehensive analysis on each of the system. With on-going restructuring of market regimes, each system is constantly evolving over time. Taking the electricity market in Great Britain (GB) as an example, it had been operating in the model of power pool for over 10 years before it reformed to a power exchange arrangement in 2001 [120–122], and in a more recent restructuring in 2014 they established the capacity market that did not exist there before [123].

Nevertheless, our general framework will remain largely stable regardless of adjustments in individual markets. This again reveals the importance of an analytical framework facing such a fast-changing area. Using the same example in GB, readers can immediately identify potential opportunities riding on the introduction of capacity market by referring to Section 3.4.

In Chapter 1, we identified three applications of flexibility management in wholesale markets, including:

- **Arbitrage in energy market**, and
- **Frequency control in ancillary services market**, and
- **Supply adequacy in capacity market**.

Correspondingly, we systemically investigate how the feasibility of these applications is influenced by different market regimes, i.e. structure of energy/ ancillary service/ capacity markets, in the reminder of this chapter. Unlike many other studies that are also focused on comparison of different market structures but for the reference of market designers, we do not analyze the full rationale behind the market design nor their comprehensive merits and drawbacks. Instead, this chapter is focused only on the differences themselves and their direct impacts on value of flexibility management solutions.

Table 3.1: List of markets involved in this study

System	Abbreviation	Country	Main Reference
PJM Interconnection	PJM	US	[18, 45, 120, 124–130]
New York ISO	NYISO	US	[124–127, 131]
Midcontinent ISO[a]	MISO	US & Canada	[125–127, 132]
ISO New England	ISO-NE	US	[125–127, 133]
California ISO	CAISO	US	[120, 125–127, 134]
Southwest Power Pool	SPP	US	[125–127, 135]
Electric Reliability Council of Texas	ERCOT	US	[18, 45, 125–127, 136]
Ontario Independent Electricity System Operator	IESO/ Ontario	Canada	[45, 124, 137]
Alberta Electric System Operator	AESO/Alberta	Canada	[45, 138]
National Electricity Market (Australia)	NEM	Australia	[18, 45, 139, 140]
National Electricity Market of Singapore	NEMS	Singapore	[45]
Germany[b]	DE	Germany	[26, 121, 141, 142]
Single Energy Market (Ireland)	SEM/ Ireland	Ireland	[121, 124]
Great Britain[c]	GB	Great Britain	[120–123, 143]
Other European Markets	-	-	[121]

[a]Formerly named Midwest ISO

[b]Referring to territories of 4 TSOs, Tennet, Amprion, 50 Hertz, TransnetBW under the regulation of Bundesnetzagentur (BNetzA) with large volume of electricity traded OTC and on power exchange, EPEX SPOT.

[c]Referring the territory of the TSO, National Grid, under the regulation of Office of Gas and Electricity Markets (ofgem) with large volume of electricity traded OTC and on power exchange, APX Power UK and N2EX .

3.2 Flexibility management in energy markets

We start our analysis from the wholesale energy market as it constitutes the central transaction platform in power markets [124].

In a competitive market price should act as an effective signal to coordinate the balance of supply and demand. Reflecting this principle in energy markets, if a market is well-designed, price volatility would increase due to lack of flexibility and in turn become an incentive to encourage participation of new flexibility sources, as introduced in Chapter 1. However, it is not always the case in reality since power market design takes into consideration for not only economic but also physical and political factors. Moreover, since market design is likely to lag behind technological development, some legacy rules tend to create barriers for new technologies even if they may already be favored by those physical, economic and political requirements.

Therefore, although energy arbitrage that can absorb energy in supply surplus and release energy in supply shortage is theoretically beneficial to power systems, it is not always feasible depending on market rules.

3.2.1 Market model: Power pool vs. power exchange

First of all, it is worthwhile to point out the difference between power pool and power exchange, since they represent two fundamentally distinct approaches of how power markets are organized.

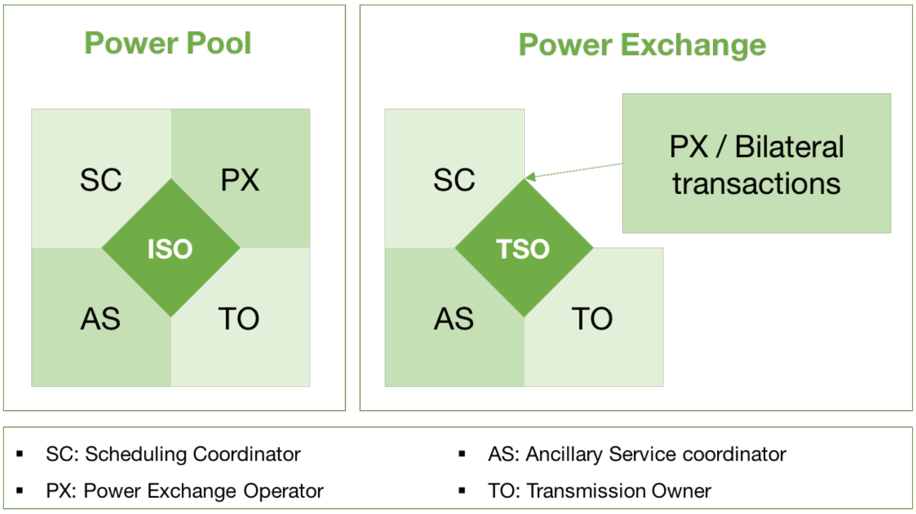

Figure 3.1: Illustration of difference between power pool and power exchange

As shown in Figure 3.1, in the model of power pool, all the structural components of power markets are integrated and coordinated by a single entity that is both market operator and system operator [18,144], often named independent system operator (ISO). Since scheduling is an integral part of the power market, schedules are determined through a single market gateway, and markets are cleared abiding by the limits of physical deliveries. In a power pool, ISO seeks to minimize the system total production cost through a centralized unit commitment to fulfill demands economically. Generators must follow the commitment schedule and the dispatch instructions issued by the ISO to receive payments [84]. Otherwise, ISO may charge penalties from the generators or suspend their participation in the power pool. Market activities are mainly on the generation-side, while demands are consolidated as input of ISOs' optimization. Players on the demand-side are usually not able to participate in the market directly unless specific measures are implemented.

In contrast, in the model of power exchange, a transmission system operator (TSO) is still responsible for scheduling coordination, ancillary service provision and transmission system operation, but power transactions are made through a power exchange organized by a third party or through bilateral contracts. Therefore, a market participant is able make electricity transactions in more than one market. As a matter of fact, power exchanges are mostly established by profit-seeking market players and have evolved from the bilateral contract model [144]. The system operator usually has no direct control on the power exchange and its role is limited to the physical aspect of maintaining system security. Each producer is responsible for self-scheduling its own units with a decentralized price-based unit commitment [84]. Therefore, power markets organized in power exchange model can be viewed to have a higher level of unbundling than those in power pool model, without invention of physical system operators in electricity trading activities.

Examples of energy markets organized in power pool:

- Most markets organized by ISOs in North America such as PJM, NY-ISO, Alberta, etc.
- Australia's NEM
- Ireland's SEM.

Examples of energy markets organized in power exchange

- most markets in European countries such as Germany, Nord Pool, GB etc.
- CAISO in the US.

Implications for flexibility management

In power exchange, the participation from supply-side and demand-side is generally symmetric and offers/bids are usually in the single form of price-quantity pairs. The physical realization of delivery is unbundled from market activities and is not concerned by market operators. This allows great freedom for flexibility players to participate in the market, regardless of whether the flexibility comes from supply- or demand- side or mixed, and which technologies are employed.

In power pool, however, generators are usually required to submit complex unit offers including physical information of resources, e.g., unit start-up and shut-down procedures, minimum-up/down time constraints, min/max power output restrictions, ramp-rate limits, transmission limits etc. [84], and participation from demand-side is generally limited. Therefore, with bundling physical and market activities, participation of flexibility is extensively under control of power pool operators. Being recognized as a generation resource or special market gateway for demand-side participation is necessary prerequisite for a new flexibility resource to directly participate in markets. Otherwise, it would be only limited to behind-the-meter applications where some flexibility resources such energy storage can complement with existing resource or load to adjust a player's position in market. In this way, the operation of flexibility might not be optimal and aggregation is impossible. In addition, due to the strong position of power pool operators, it is less likely for players to gain market power than in power exchange.

Overall, there are greater limits for market participation of flexibility management in power pool than in power exchange. Technology vendors need to go further in their efforts aligning market rules and regulatory environment for business planning in power pools.

3.2.2 Marketplace

In most regions, the energy market consists of several marketplaces along the timeline, as shown by Figure 3.2[1].

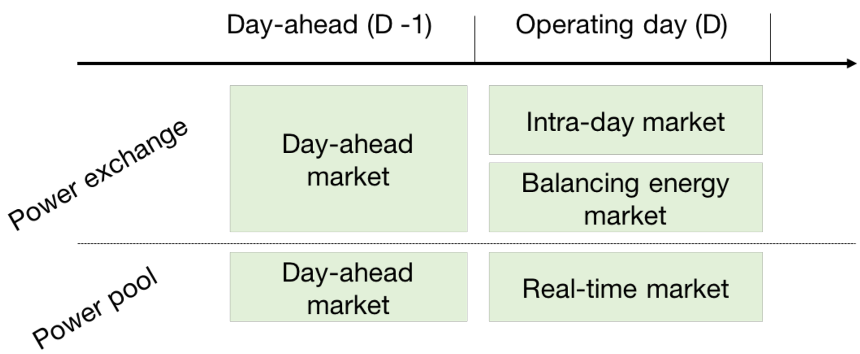

Figure 3.2: Typical marketplaces in wholesale energy market

In markets organized with power exchange model, large volumes of energy are usually traded in day-ahead (DA) market. Intra-day (ID) market, which can be viewed as an extension of day-ahead spot market bringing gate closure near delivery, is a common measure to mitigate increasing needs of real-time balancing operations, as introduced in Chapter 1. All deviations from the commitment scheduled by DA and ID markets requires balancing energy delivery that is coordinated by system operators and are settled through a third marketplace, often named balancing energy market. Imbalance settlements that are accounted in the balancing energy market involve two mechanisms: first, the deviation of one player can be somehow offset by opposite deviations of other players; second, on the system level, the aggregated imbalance is settled by activating frequency control services. In most market regimes, system operators will play a centralized role to clear and settle costs incurred from both mechanisms, while sometimes system

[1] Forward products are excluded since financial derivative markets are out of our scope; refer to Chapter 1.

operators may allow ex-post trading between market players regarding the imbalance settlement through the first mechanism such as the Swiss and Greek power markets.

Slightly different arrangements are adopted in power pools. Since delivering balancing energy is the responsibility of the same entity that operates the energy markets, real-time markets are used for settlements of both post-DA scheduling adjustments and balancing operations.

The three-settlement market (i.e. day-ahead, intra-day and balancing market) is the European Union target electricity model [145] so has been implemented in most European energy markets such as Germany, France, Denmark, GB, Italy, Spain, etc. Two-settlement market (i.e. day-ahead and real-time market), on the other hand, is a common practice in North America [124].

Generally, arbitrage in DA market is less favorable for emerging flexibility players, due to relative low volatility and dominance of large conventional generation companies. Flexibility management shall gain more advantage in market closer to delivery due to its comparative competence of fast response and operations to conventional generators.

Nonetheless, participation in any marketplace to perform arbitrage is potentially profit-making. Therefore, identifying which marketplaces exist and whether they are accessible is a necessary step for valuing the opportunities of flexibility management.

3.2.3 Pricing scheme

If a marketplace is accessible for flexibility players, a further concern would be the profitability of arbitrage. Since arbitrage is essentially a game played with prices, the pricing mechanism is of most importance, which is however highly diverse across different markets.

Nodal pricing vs. zonal pricing

With nodal pricing scheme, prices at each network node are different. On the contrary, uniform pricing scheme applies same price everywhere in the whole control area. Zonal pricing as a trade-off between these two schemes, use the same price in a particular zone including a bundle of nodes.

Nodal pricing internalizes network congestion in price formation. If congestion restricts lowest-cost electricity being transmitted to a particular location, electricity with higher cost but no congestion is dispatched and consequently price at that location will rise. Nodal pricing has clear benefits [146] but it is harder to implement, especially in markets arranged in power exchange where market operators have no insight into the physical system[2].

[2] In these regions, it is possible to implement nodal pricing in balancing markets that

Nodal pricing is adopted in many systems in North America, such as PJM, CAISO, NYISO, ISO-NE etc., using a mechanism named locational marginal price (LMP) model. Zonal pricing is used in Australia's NEM and other energy markets organized in power exchange model.

Nodal pricing incorporates the consideration of congestion. The value of T&D congestion relief can theoretically be partially captured by arbitrage, especially using flexibility technologies that are easier to be deployed at smaller scale in particular locations such as batteries. However, for aggregators, nodal pricing increases the operational complexity.

Time resolution

Since RES generation is intermittent and may vary significantly in a short time interval so may the residual load. As a result, a higher time resolution of pricing can better represent the market need for flexibility. Emerging flexibility solutions with faster response and higher ramp rate shall gain advantages with higher pricing resolution in theory. However, it should be noted that the pricing and dispatching time interval is sometimes different to the settlement interval. For example, the real-time markets in PJM has 5-min pricing resolution but settlement of energy delivery is accounted at hourly resolution [148]. In such an arrangement, arbitrage against the original price signals may be activated for price differences within a settlement interval, which brings no revenue. Therefore, the operational plan of arbitrage should be determined based on estimation of prices for actual settlement.

3.3 Flexibility management in ancillary service markets

Among all ancillary services, this thesis is particularly focused on frequency control services that are used to tackle imbalance between supply and demand by delivering balancing energy, as introduced in Chapter 1. Frequency control services are usually the most costly among all ancillary services and relying on services provision from market players, while there are usually no markets for other ancillary services such as voltage support, loss compensation, black start etc [120, 124].

In different regimes, there exist many differences regarding how frequency control services are defined, procured and operated, as well how the cost is allocated and recovered. Understanding these differences allows technology vendors know which services can be provided using flexibility and to whom they can sell flexibility solutions.

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is coordinated by physical system operators, as illustrated by a research project [147]. However, we have not seen any large-scale practice in reality.

3.3.1 Terminology for frequency control services

Different terminologies used in different power jurisdictions may easily lead to confusion while comparison between different regimes is to be made. Different terms are often used to refer to the same service, while in some instances the similar terms may refer to two disparate services in different regimes. For example, secondary control reserve (SCR) and automatic frequency restoration reserve (aFRR) (both used in European markets) are interchangeable concepts. On the contrary, primary reserve in North America is often used to distinguish services from supplementary reserve, while it is closer to the concept of tertiary reserve rather than primary reserve used in Europe.

Generally, these terminologies can be classified into two groups as they follow the guidance of service definitions from the Federal Energy Regulatory Commission (FERC) and the Union for the Coordination of the Transmission of Electricity (UCTE). According to the functioning mechanism[3], terminologies in these two systems can be mapped into a a comparison framework show by Table 3.2.

Table 3.2: Terminology for frequency control reserves in various regimes [120, 125, 146]

UCTE terms	*Equivalents*	**FERC terms**	*Equivalents*
Primary control reserve (PCR)	Frequency containment reserve (FCR)	Frequency response	
Secondary control reserve (SCR)	Automatic frequency restoration reserve (aFRR)	Frequency regulation	
Tertiary control reserve (TCR)	Manual frequency restoration reserve (mFRR)	Spinning reserve	Synchronous reserve
		Non-spinning reserve	Non-synchronous reserve/ Quick-start reserve
		Supplemental reserve	Replacement reserve

It shall be noted that in terms of activation time, UCTE has specifically defined that:

- Primary reserve shall be automatically activated within 30s;
- Secondary reserve need to be completely delivered within 15 minutes;
- Tertiary reserve shall start within 15-20 minutes after received the order from system operators.

[3] PCR refers to response activated locally by a speed governor fitted in generator. SCR is activated by a centralized control signal named automatic generation control (AGC) signal. TCR follows manual orders from system operators [125].

In contrast, the time framework for each service category is not aligned among markets in North America [125], but generally, activation time of frequency regulation is comparable to an in-between state of primary and secondary control reserve.

In addition, there are no markets for frequency response in North America [120, 125] that are equivalent to primary control reserve markets in Europe.

Generally, new flexibility solutions have advantages for services with shorter activation time and shorter duration compared to service providers using conventional generation. Therefore, frequency control services can be roughly ranked in accordance with the extent to which they are suited to emerging technologies, from most to least: primary, secondary and tertiary. However, this is case-specific depending on characteristics of specific technologies and markets, so is not discussed in details here.

3.3.2 Procurement and cost allocation

Usually, markets for frequency control services involve trading for two commodities, i.e. capacity and energy, as shown by Figure 3.3.

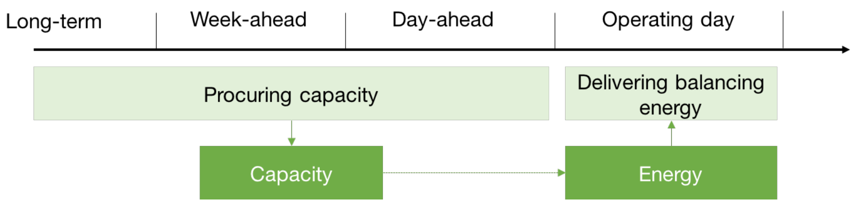

Figure 3.3: Illustration of markets and activities related to frequency control services

Capacity refers to a commitment that service providers make to system operators, that they will keep reserves ready to be dispatched for real-time operations. The requirement for capacity is determined by the system operator and procured ahead of real-time operation. Specifically, in the continental European synchronously interconnected system, a total PCR of 3000 MW needs to be provided according to the rules of the European Network of Transmission System Operator (ENTSO-E), while amounts of necessary SCR and TCR capacity are determined by each TSO [149]. For instance, in Germany, TSOs run a quarterly assessment process to dimension the provision of SCR and TCR for next three months [141]. In North America, ISOs determine the need for reserve capacity by conducting their own processes, so-called reliability assessment, which take place after gate closure of day-ahead market and before each operating hour [125].

Energy is what services providers actually deliver to the system upon activation by system operators in real time. The amount of energy is determined based on physical needs for grid balancing.

The acquisition and settlement process for the frequency control capacity and energy also varies amongst different market regimes.

Generally, two models are identified. We name them as centralized procurement and decentralized procurement respectively; see Figure 3.4.

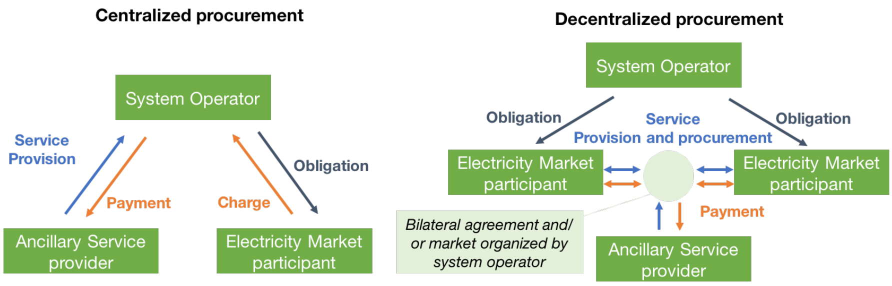

Figure 3.4: Two models for procurement and cost allocation of frequency control services

In the centralized model, the system operator is designated as the single buyer [120]. System operators (SO) will either organize auctions in short term ahead of the operating day, e.g. German TSOs organize weekly-ahead auctions for SCR and day-ahead auctions for TCR [141], or seek long-term bilateral contract with service providers, e.g. Australian Energy Market Operator (AEMO) uses this approach to organize ancillary services in NEM [150]. On the other hand, SOs need to recover costs incurred by charging entities with obligation. In different markets and for disparate services, obligations are assigned in various ways. For example, costs for energy of frequency control services in Germany and for regulation reserve in Australia are recovered from entities who violate their commitments determined in energy markets, while costs for capacity of frequency control services in Germany and for contingency reserve (similar to TCR) in Australia are socialized among all market participants.

Decentralized model is adopted by ISOs in North America. In this model, ISOs allocate requirements for reserve capacity to market players according to their servicing loads to the system total load [120,125,129]. Market players have to fulfill their own obligations through self-supplied reserve, through bilateral contract with other market participants, and/or through purchases of reserve in some form of reserve market organized by ISO [125]. In this way, market participants in the power market are put into competition for procuring frequency control services. Examples using this model include all seven ISOs in the US.

Flexibility solutions can be employed for the provision of frequency control services and for fulfilling obligations in both arrangements. However, while provision and obligation fulfillment are symmetric in the decentralized approach, there might be asymmetry in the centralized approach with SOs standing in-between. Payments may differ between services provided for SOs and for market players to fulfill their obligations.

3.3.3 Frequency control product design

Further to the high-level distinctions mentioned previously, attentions should also be paid to some key details regarding how the frequency control service as products are designed. Product design will significantly affect the feasibility and profitability of certain technologies providing frequency control services. Without mentioning too many technological specifications, we discuss four points here.

First of all, pre-qualification of resources to provide a given service is necessary. While activation time is usually an advantage of emerging flexibility solutions, duration of dispatch tends to be a bottleneck, especially for tertiary control reserves. For instance, CAISO requires a minimum of 30 minutes duration for delivering spinning and non-spinning reserves and duration of providing tertiary reserve for German TSOs is in 6-hour blocks. In these cases, some flexibility solutions, such as flywheel energy storage that is only able to last for about 15 minutes [125, 151], are excluded from provision of those services.

Second, frequency control services are sometimes divided into up and down services. Up services mean there are generation shortage and injection of energy or reduction of demand are required. On the contrary, down services refer to situations where more demand or less generation is needed. Separate markets for these two types of services would allow more choices for flexibility players to make optimal offers in accordance of the technological characteristics of their flexibility resources.

Besides, it is of a concern how automatic frequency control signals are engineered. For example, an energy storage device that does not generate energy will favor a signal that is energy-neutral to it, i.e. the state of charge of the device can come back to its initial value after a period of operation.

Finally, one should consider how services are priced. Capacity commitment and actual delivery, i.e. amount of released energy and sometimes performance as well, are normally priced and settled separately. Since flexibility management solutions have the potential to outperform conventional flexibility solutions considering their technological characteristics of fast response and high ramp rate, a pricing scheme where performance of delivery is valued tends to offer merits for emerging flexibility solutions. By this rationale, the FERC requires ISO markets to compensate for regulation based on actual service provided according to its Order 755 [152]. Some ISOs including PJM, NYISO, ISO-NE followed the order to establish such a mechanism. Nevertheless, in most market regimes, only amount of energy is accounted for final payment for frequency control services.

More detailed impact of product design and technical implications will be discussed in Chapter 5.

3.4 Flexibility management in capacity markets

The capacity market is established in some power market jurisdictions to minimize investment risks of power generators so that resource adequacy can be effectively ensured. Investors are remunerated for commitment to keep capacity online. However, it is not a common practice, because of complex political reasons which are not our focus in this thesis, but it is worth to mention briefly that ensuring minimal investment risk for generators means risks are somehow shifted to consumers [124].

However, for flexibility players and technology vendors, the existence of capacity market is generally favorable as it potentially provides a direct revenue stream. Naturally, one should examine which technologies are suitable and whether demand-side resources are qualified to receive remuneration.

Examples of power market jurisdictions with capacity market include PJM, NYISO, ISO-NE, Spain, Ireland, GB (since 2014), etc. Also, transition from an energy-only market towards a capacity market has been observed in some markets, e.g. Ontario IESO and Alberta AESO are in the process of developing a capacity market, initiated in 2014 and 2016 respectively.

In energy-only markets, system operators have sometimes taken alternative measures to ensure adequacy, e.g. strategic reserves or named emergency products. Strategic reserves and emergency products are either generation capacity or curtailable loads that are activated only when scarcity of generation is observed (typically reflected by extremely high prices).

Energy-only markets with such capacity remuneration mechanisms include: ERCOT, Australia's NEM, Germany, Nord Pool, Belgium etc.

Finally, for markets without any of these capacity measures mentioned above, it is likely for extreme prices to occur, which will be an indirect incentive for flexibility players' arbitrage in energy markets.

3.5 Aggregator and demand-side participation

Participation of aggregators and other providers of demand-side flexibility is not always allowed in some marketplaces. This is especially an issue for ancillary services and capacity markets as they were initially designated only for generation resources. Participation in energy markets may also be limited in power pool arrangement as discussed previously. Therefore, it is of great importance to examine the market rules regarding this issue.

So far, examples of power pools that allow participation of aggregators and demand-side responses in energy market include: PJM, ISO-NE, Ontario IESO, Singapore and Australia's NEM (as of April 2017 [46]), etc.

Examples of jurisdictions allowing participation of aggregators and demand-side responses in frequency control ancillary service market include: PJM, Ontario, Singapore, Alberta AESO, ERCOT, Australia's NEM, etc.

Examples of capacity markets that have remuneration programs for demand-side resources include: PJM, ISO-NE.

Examples of energy-only market that have strategic reserve of emergency products for demand-side resources include: ERCOT, Australia's NEM, Nord Pool, Germany, etc.

3.6 Summary and the analytical framework

From the analysis presented above, it is clearly seen that investigating opportunities for flexibility management across different market regimes is indeed a sophisticated task since many layers of hierarchy exist in terms of structural differences across markets. In order to better guide technology vendors for qualitative assessment of flexibility management in a given regime, we organized the previous analysis into analytical frameworks illustrated by Figure 3.5-3.7. We apply these frameworks for our own analysis in the reminder of this thesis.

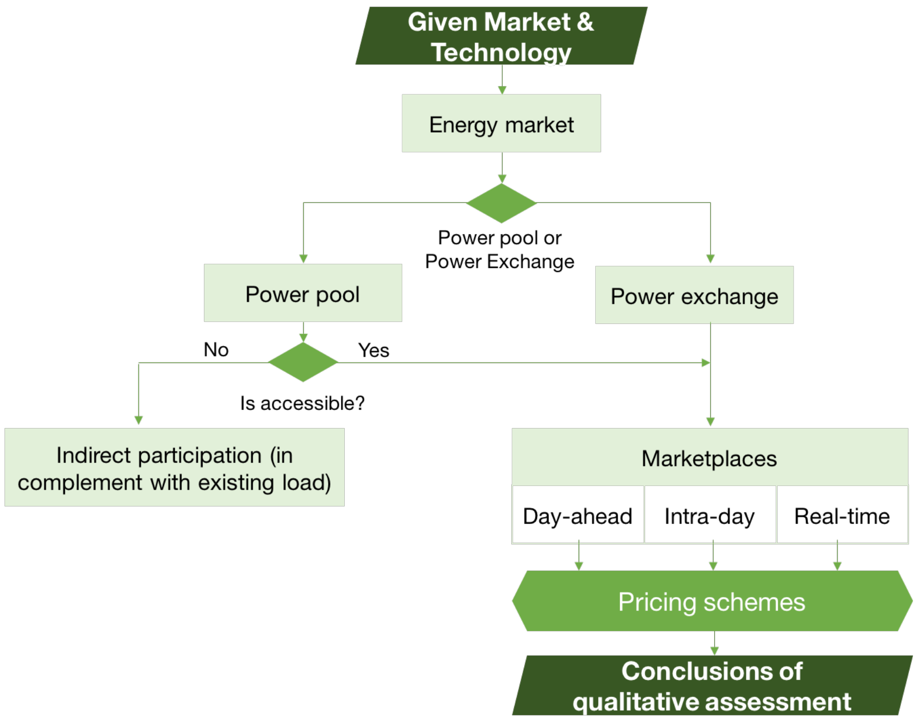

Figure 3.5: Analytical framework for qualitative analysis of flexibility management in energy market

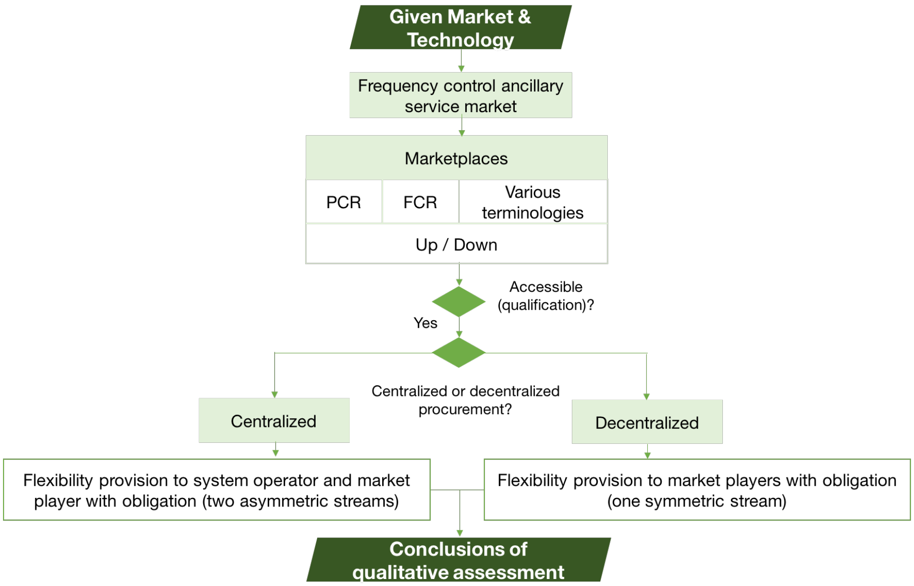

Figure 3.6: Analytical framework for qualitative analysis of flexibility management in frequency control market

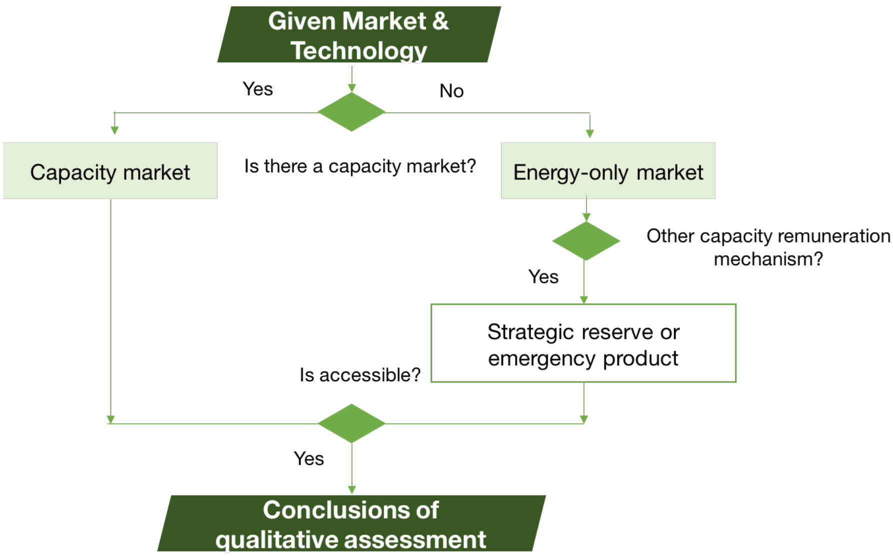

Figure 3.7: Analytical framework for qualitative analysis of flexibility management in capacity market

Chapter 4

Methodology for The Quantitative Valuation of Flexibility Solutions

This chapter presents the methodology for quantifying the value of flexibility solutions. A modular approach is adopted to overcome the complexity from multi-dimensional market-technology contexts. A total of 6 modules are developed, being categorized into two groups, i.e. market- and technology- based modules. We first introduce each of the modules and then explain how these modules are organized within an optimization.

4.1 Modular approach to build valuation models

As discussed in Chapter 1, the quantitative work of this thesis aims at determining the market size and profitability of different flexibility solutions in various power market jurisdictions. By combing methodologies of other similar works reviewed in Chapter 2 and our own analytical frameworks established in Chapter 3, we develop a techno-economic model for the quantitative analysis.

Since there are structural differences existing between technologies and between markets as we have seen in previous chapters, the model needs to be implemented in several modes. For instance, for m technologies in n market regimes, a total of $m \times n$ modes is required. In order to avoid redundancy and make the model easier to reuse and maintain in the future, we adopt a modular approach, breaking up the model into several modules with each module having dependencies on either technology or market. Using the same example, each module needs either m or n modes. 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

Table 4.1: List of modules

Section	Module name	Input	Output
Market-based modules			
4.2.1	Revenue	Price signals; Frequency control signals; Sets of targeted marketplaces	Matrix of coefficients for revenue calculation
4.2.2	Market simulation	Generation time-series by fuel type; Consumption time-series	Price and volume signals
4.2.3	Market constraints	Volume signals	Constraints for optimization
Technology-based modules			
4.3.1	Cost	Investment cost; Designed life time; Operating life time; System state	Matrix of coefficients for cost calculation
4.3.2	Technology simulation	Efficiencies of charge, discharge and storage; Maximum charge, discharge rates; Energy-to-power ration	Matrix of coefficients to determine system states
4.3.3	Technology constraints	System size, system state	Constraints for optimization

outputs. The working flow of the model is illustrated by Figure 4.1. It should be noted for market-based modules there are two modes, i.e. using actual price-volume data as input or using simulated price-volume signals as input. The rationale of implementing these two modes will be discussed later in Section 4.2.2.

Using this model, we can quantify the revenue and cost associated with the deployment of a given flexibility solution in a selected market and thus evaluate the profitability with any given scales of flexibility management system in the power market. By taking into account market constraints including liquidity, marginal revenue with respect to system scale will drop when liquidity becomes scarce. This allows us to derive the maximum revenue potential in a market. Furthermore, impacts of renewable penetration and cost reduction that are raised in our initial research questions can be assessed since the share of renewable resources in generation mix and the cost parameters of flexibility systems are all made to be variables of the model.

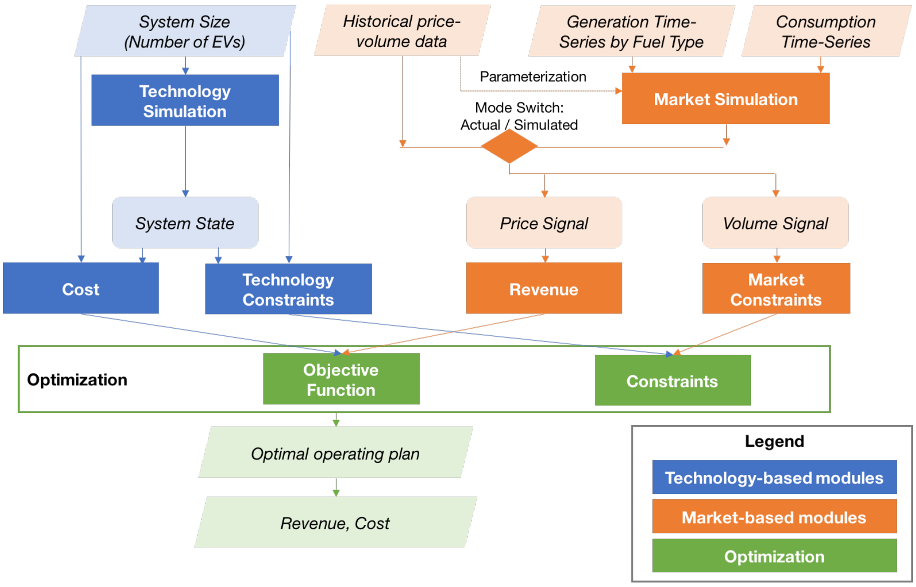

Figure 4.1: Flow chart of the techno-economic model

4.2 Market-based modules

4.2.1 Revenue module

As determined in the scope, we only quantify explicit revenues from arbitraging in energy markets and providing frequency control services in ancillary service markets in this thesis.

In each business case, trading can be performed in one, or more than one marketplace. By denoting the set of selected marketplaces for energy arbitrage as $\mathbb{I}$ and index each marketplace as i, we can represent each of I selected marketplaces as:

$$i \in \mathbb{I} = \{1, 2, \ldots, I\} \tag{4.1}$$

where a marketplace i could refer to day-ahead market or intra-day market or others; see Section 3.2

Applying the same exercise for frequency control services, we have the selected marketplaces in ancillary service markets denoted as:

$$j \in \mathbb{J} = \{1, 2, \ldots, J\} \tag{4.2}$$

where a marketplace j could be the marketplace for PCR or SCR or others, referring to Section 3.3.

For energy arbitrage, we need to determine at each time step t in a certain marketplace i, the amount of energy to sell, denoted as $e^{+}_{t,i}$ in MWh, and the amount of energy to buy, denoted as $e^-_{t,i}$ also in MWh. The price signal at that marketplace is indicated as $\pi_{t,i}$ in USD/MWh[1].

In frequency control service, what is to be decided by the operator of flexibility resources is the amount of capacity offered in a certain marketplace j at each time step t, denoted as $c_{t,j}$ in MW, the price of which is denoted as $\psi_{t,j}$ in USD/MW. The amount of energy delivered for frequency control services is determined upon request of system operator via the control signal. We represent the control signal for frequency control service in a marketplace j at each time step t as a ratio between the required energy and committed capacity, denoted as $\delta_{t,j}$ in MWh/MW. The price for the energy delivery is denoted as $\phi_{t,j}$ in USD/MWh. As introduced in Section 3.3, in some market regimes, the performance will be considered in payment for frequency control service. Since evaluating performance could be a complex manner, we make some assumptions in specific cases and reflect the performance payment in the price signal $\phi_{t,j}$.

Thereby, we can finally calculate the total revenue R from all marketplaces over a period of time $\mathbb{T}$ ($t \in \mathbb{T} = \{1, 2, \ldots, T\}$) as:

$$R = \sum_{t}^{t\in\mathbb{T}} R_t = \sum_{t}^{t\in\mathbb{T}} \left(\sum_{i}^{i\in\mathbb{I}} \pi_{t,i}(e^+_{t,i} - e^-_{t,i}) + \sum_{j}^{j\in\mathbb{J}} (\phi_{t,j}\delta_{t,j} + \psi_{t,j})c_{t,j} \right) \tag{4.3}$$

In this equation, $e^+_{t,i}$, $e^-_{t,i}$ and $c_{t,j}$ are decision variables of the optimization problem to find a optimal operating plan. $e^+_{t,i}$, $e^-_{t,i}$ and $c_{t,j}$ are all non-negative values, i.e.:

$$e^+_{t,i}, e^-_{t,i}, c_{t,i} \geq 0 \quad \forall t \in \mathbb{T},\ \forall i \in \mathbb{I},\ \forall j \in \mathbb{J}$$

Price signals $\pi_{t,i}$, $\phi_{t,j}$ and $\psi_{t,j}$ and frequency control signals $\delta_{t,j}$ are inputs of the revenue module. $\mathbb{I}$ and $\mathbb{J}$ are determined according to the business case to be studied. For example, we can set $\mathbb{I} = \{Day\ ahead\ market\}$ and $\mathbb{J} = \emptyset$ in order to value arbitrage in day-ahead energy market.

For the ease of implementation, we re-formulate Equation (4.3) as:

$$R = \mathcal{R} \cdot X \tag{4.4}$$

where X is the vector for all decision variables. With $i \in \mathbb{I} = \{1, 2, \ldots, I\}$, $j \in \mathbb{J} = \{1, 2, \ldots, J\}$ and $t \in \mathbb{T} = \{1, 2, \ldots, T\}$, X can be derived by following the steps:

[1]Other currencies used in certain markets, e.g. AUD in Australia's NEM, are convert to USD based on currency exchanged rates. Details will be provided in Section 5.3.1.

- Formulating the time-series of energy to be sold, energy to be bought and reserve capacity in each marketplace into vectors:

$$E_i^+ = \begin{bmatrix} e_{1,i}^+ \\ e_{2,i}^+ \\ \vdots \\ e_{T,i}^+ \end{bmatrix} \quad E_i^- = \begin{bmatrix} e_{1,i}^- \\ e_{2,i}^- \\ \vdots \\ e_{T,i}^- \end{bmatrix} \quad C_j = \begin{bmatrix} c_{1,j} \\ c_{2,j} \\ \vdots \\ c_{T,j} \end{bmatrix} \tag{4.5}$$

- Connecting the vectors for each marketplace together:

$$E^+ = \begin{bmatrix} E_1^+ \\ \vdots \\ E_i^+ \\ \vdots \\ E_I^+ \end{bmatrix} \quad E^- = \begin{bmatrix} E_1^- \\ \vdots \\ E_i^- \\ \vdots \\ E_I^- \end{bmatrix} \quad C = \begin{bmatrix} C_1 \\ \vdots \\ C_i \\ \vdots \\ C_I \end{bmatrix} \tag{4.6}$$

- Finally connecting all vectors to obtain X as:

$$X = \begin{bmatrix} E^+ \\ E^- \\ C \end{bmatrix} \tag{4.7}$$

Matrix $\mathcal{R}$ can be obtained by following similar steps:

- Formulating the time-series of price signals in each marketplace into vectors:

$$\begin{aligned} \Pi_i &= \begin{bmatrix} \pi_{1,i} & \pi_{2,i} & \dots & \pi_{T,i} \end{bmatrix} \\ \Phi_j &= \begin{bmatrix} \phi_{1,j} & \phi_{2,j} & \dots & \phi_{T,j} \end{bmatrix} \\ \Psi_j &= \begin{bmatrix} \psi_{1,j} & \psi_{2,j} & \dots & \psi_{T,j} \end{bmatrix} \end{aligned}$$

- Connecting the vectors of price signals for each marketplace together:

$$\begin{aligned} \Pi &= \begin{bmatrix} \Pi_1 \mid & \dots \mid & \Pi_i \mid & \dots \mid & \Pi_I \end{bmatrix} \\ \Phi &= \begin{bmatrix} \Phi_1 \mid & \dots \mid & \Phi_j \mid & \dots \mid & \Phi_J \end{bmatrix} \\ \Psi &= \begin{bmatrix} \Psi_1 \mid & \dots \mid & \Psi_j \mid & \dots \mid & \Psi_J \end{bmatrix} \end{aligned}$$

- Creating a diagonal matrix using frequency control signals:

$$\Delta = diag(\delta_{1,1}, \delta_{2,1}, \dots, \delta_{T,1}, \delta_{1,2}, \delta_{2,2}, \dots, \delta_{T,2}, \dots, \delta_{T,J}) \tag{4.8}$$

- Finally $\mathcal{R}$ is calculated as:

$$\mathcal{R} = \begin{bmatrix} \Pi \mid & -\Pi \mid & \Phi \cdot \Delta + \Psi \end{bmatrix} \tag{4.9}$$

Summary

A high-level summary about the key information for revenue model is provided as listed below:

Summary of revenue module
Decision variable: X **Input:** Price signals: Π, Φ, Ψ Frequency control signal: Δ Selected marketplaces: $\mathbb{I}$, $\mathbb{J}$ **Output:** Coefficient matrix: $\mathcal{R}$

4.2.2 Market simulation module

As discussed in Section 2.2.2, using historical data of price as input is a common exercise, which offers a pragmatic way to derive reference values that are valid in near future. This method is also adopted in this thesis to do valuation under current market conditions. However, using historical data as fixed input prevents us from understanding a long-term trend with potential changes, among which we are particularly interested in the impact of renewable penetration, i.e. increasing share of RES in generation mix. To overcome the limitation of using historical price signals, we developed this market simulation module for generating future price scenarios but only for valuation of energy arbitrage as discussed in Section 2.2.2.

In Chapter 2, we have illustrated that our questions are not perfectly answered in the literature. We are interested in both long-term price trends over a relative large scope of time as well as short-term price movement in high time resolution. In the literature, the former is usually evaluated using a deterministic merit-order model and the latter is often simulated using a stochastic SARIMA model, as discussed in Section 2.2.2. We combine these two approaches. In order to simulate prices in energy markets, we first use the merit-order model to get a determinant price signal in day-ahead market, denoted as $\tilde{\pi}$. The actual price signals, denoted as π, in day-ahead as well as in other energy markets, e.g. intra-day and real-time, are largely dependent on the merit-order price. Deviations may come from various factors and we tackle them purely in a statistical way by viewing them as stochastic processes and simulating them in the SARIMA model. We denote the stochastic part of the price as $\dot{\pi}$. Thereby, the output of market simulation model is the combination of output from merit-order model and SARIMA model, as shown below:

$$\pi = \tilde{\pi} + \dot{\pi} \tag{4.10}$$

In actual implementation, the merit-order model and SARIMA model are first parameterized using historical data, see Figure 4.2.

Compared to other studies working on merit-order models, this thesis has a particular focus on flexibility so we categorize the capacity of generation into four classes considering their impacts on overall system flexibility. These four classes are non-dispatchable RES, inflexible, middle and peak generations. As discussed in Chapter 1, RES generation is often taken out separately and compared to the consumption, to get the so-called residual load. The other three classes are obtained by running a algorithm that is originally developed in this thesis and is able to analyze power plants' level of flexibility. Using the classified generation, residual load as well as the historical price data, regressions are performed to determine the parameters of the merit-order model.

Thereafter, we further compared the actual price data and the fitted price derived from the merit-order model. With the concern that regressions will eliminate the stochastic movement of price and reduce the price volatility which impact the value of arbitrage, we further parameterize a SARIMA model to re-capture the eliminated stochastic price movement.

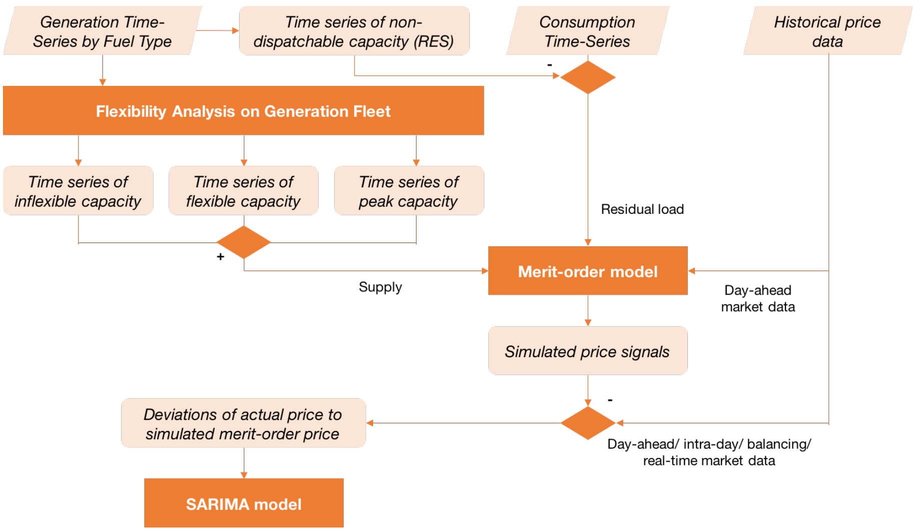

Figure 4.2: Parameterization of the merit-order model and SARIMA model

With these two model, we can then simulate price signals for different scenarios where the time-series of supply and consumption are generated based on a given scenario (Figure 4.3). Details of these two sub-models

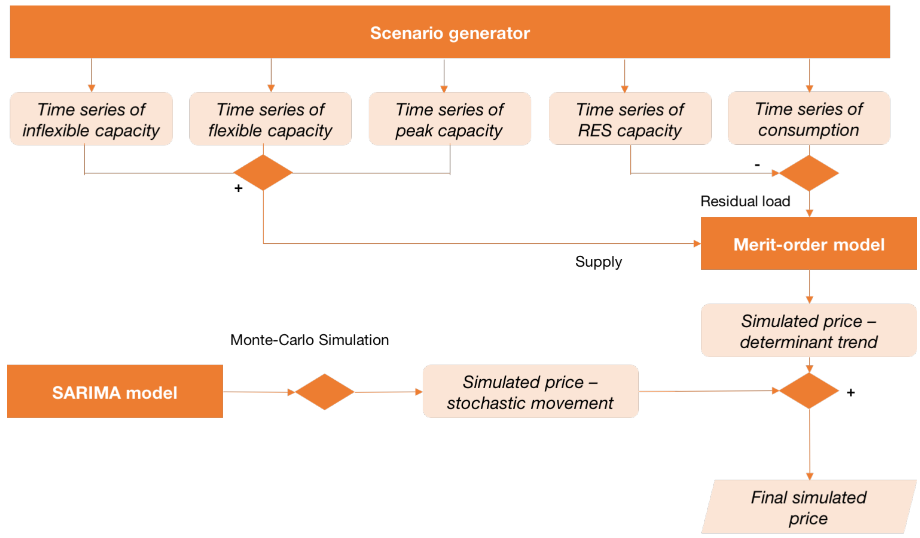

Figure 4.3: Simulation of price using the merit-order model and SARIMA model based on given scenario

together with the algorithm of flexibility analysis of generation fleet are introduced in the reminder of this section.

Flexibility analysis on generation fleet

In Chapter 1, we mentioned that increasing share of RES in total generation mix will raise the need for flexibility. Lack of flexibility will possibly lead to negative market prices, and high price volatility in wholesale energy markets. The mechanism behind these observations are modeled here by investigating the flexibility of different types of power plants.

The flexibility of a power plant can be characterized by three key features [40]:

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

A graphic illustration is provided by Figure 4.4.

If a power plant can adjust its load from zero to nominal capacity within a time interval in the day-ahead market (typically 1 hour), it can be deemed to have unlimited flexibility in the day-ahead market. This applies to many types of generation technologies, such as hydro, electrochemical systems and gas turbines [9, 40, 153, 154]. However, for power plants using steam

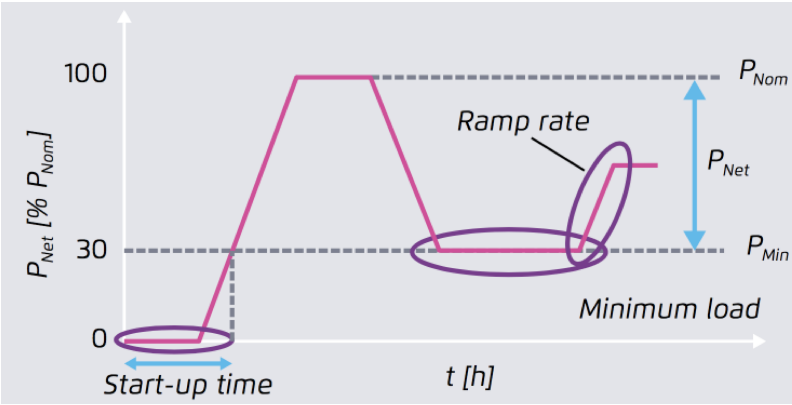

Figure 4.4: Illustration of key flexibility parameters of a power plant [40]

turbines, e.g. coal, lignite and nuclear power plants, their ability to adjust output within short time interval is limited. For a steam-turbine power plant, a cold start (starting from standstill) may take up to 100 hours or at least 4 hours even with the state-of-the-art thermal power plants [9] and the minimum operational load is about 25-60% of its nominal capacity [40]. Therefore, in order to avoid cold starts that lead to long-time shutdown, steam-turbine power plants have to keep a minimum output, which leads to hard inflexibility. Furthermore, even within the overall bandwidth of operation, steam-turbine power plants may not be able to ramp to any given level of output due to relative slow ramp rate [9]. Therefore, for those conventional power plants, their flexibility is bounded within a certain time interval. We refer to these power plants as *flexibility-limited*.

In order to quantitatively model the effect of inflexibility, we need to quantify the amount of capacity by its level of flexibility. An algorithm is therefore developed. In the algorithm, we take the whole of all power plants with the same fuel type in a power system as the basic unit system, denoted as f. The overall generation fleet can be then viewed as a set of these unit systems, denoted as $\mathbb{F}$. For each $f \in \mathbb{F}$, if it belongs to the flexibility-limited generation as discussed above, we will run the procedure listed below and illustrated graphically by Figure 4.2.2:

1. Make the duration curve using the generation data of a given fuel type f, e.g. generation of all coal-fired power plants in a power system, over

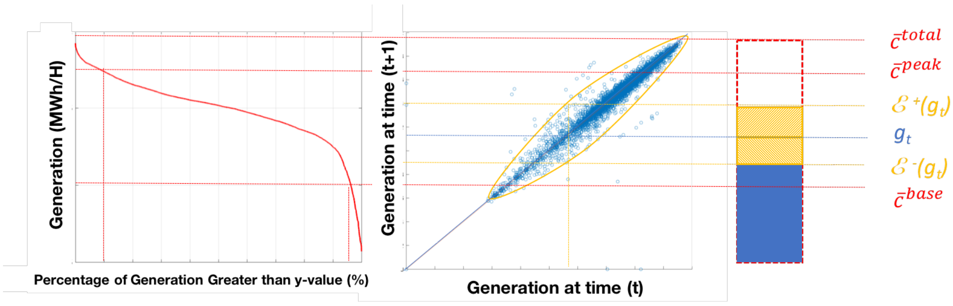

Figure 4.5: Schematic illustration of determining bounded flexibility for limited flexible generations

a given period.

2. From the duration curve, determine two time invariants, $\bar{c}_f^{\text{peak}}$ and $\bar{c}_f^{\text{base}}$. The term $\bar{c}_f^{\text{peak}}$ represents the capacity that is operated for only a small percentage (e.g. 10%) of time so can be viewed as the capacity that would be only activated for peak hours (e.g. 2.4 hours per day with the percentage being 10%), and $\bar{c}_f^{base}$ is the capacity operated for all time so represents the base load. However, since in the real world there are always data defects, we would set a threshold to exclude the outliers.

3. Compare the generation at each time time t, denoted as $g_{t,f}$, to the generation at next time step $t+1$, denoted as $g_{t+1,f}$. As analyzed previously, for flexibility-limited power plants, $g_{t+1,f}$ will be bounded within a certain range. Therefore, we determine the envelop lines of $g_{t+1,f}$ as functions of $g_{t,f}$. By denoting the upper envelop line as $\mathcal{E}_f^{+}(\cdot)$ and the lower envelop line as $\mathcal{E}_f^{-}(\cdot)$, we have:

$$\mathcal{E}_f^{-}(g_{t,f}) \leq g_{t+1,f} \leq \mathcal{E}_f^{+}(g_{t,f})$$

4. Thereby, based on the generation data at time $t-1$, we can derive for the next time step:

   - Inflexible capacity, denoted as $\tilde{c}_{t,f}^{\text{inflex.}}$. It is the minimum capacity that cannot be abated, calculated as:

   $$\tilde{c}_{t,f}^{\text{inflex.}} = \max\{\mathcal{E}_f^{+}(g_{t,f}),\ \bar{c}_f^{\text{base}}\}$$

   - The available capacity serving peak hours, denoted as $\tilde{c}_{t,f}^{\text{peak}}$. It is the part of maximum reachable capacity $\mathcal{E}_f^{+}(g_{t,f})$ beyond $\bar{c}_f^{\text{peak}}\}$ so can be calculated as:

$$\tilde{c}_{t,f}^{\text{peak}} = \max\{0,\ \mathcal{E}_f^+(g_{t,f}) - \overline{c}_f^{\text{peak}}\}$$

- Middle capacity, denoted as $\tilde{c}_{t,f}^{\text{mid.}}$. It is the range of output can be flexibly adjusted and between inflexible and peak load, computed as:

$$\tilde{c}_{t,f}^{\text{flex.}} = \min\{\mathcal{E}_f^+(g_{t,f}),\ \overline{c}_f^{\text{peak}}\} - \overline{c}_f^{\text{inflex.}}$$

If a generation type is categorized as flexibility-unlimited generation, as discussed previously, the production at each time step $g_{t,f}$ can be adjusted to any targeted value between 0 to full capacity, denoted as $\overline{c}_f^{\text{total}}$. Therefore, for these types of generation, we have

$$\mathcal{E}_f^-(\cdot) \equiv 0$$

$$\mathcal{E}_f^+(\cdot) \equiv \overline{c}_f^{\text{total}}$$

By performing the flexibility analysis on the generation fleet, we can then classify the total supply capacity at each time step into three categories by the level of flexibility, i.e. inflexible capacity, flexible capacity and peak capacity, shown as below:

$$\tilde{C}_t^{\text{inflex.}} = \sum_f^{f\in\mathbb{F}} \tilde{c}_{t,f}^{\text{inflex.}} \tag{4.11}$$

$$\tilde{C}_t^{\text{mid.}} = \sum_f^{f\in\mathbb{F}} \tilde{c}_{t,f}^{\text{mid.}} \tag{4.12}$$

$$\tilde{C}_t^{\text{peak}} = \sum_f^{f\in\mathbb{F}} \tilde{c}_{t,f}^{\text{peak}} \tag{4.13}$$

The total available capacity at time t is then represented as:

$$\tilde{C}_t^{\text{total}} = \tilde{C}_t^{\text{inflex.}} + \tilde{C}_t^{\text{mid.}} + \tilde{C}_t^{\text{peak.}} \tag{4.14}$$

Merit-order model

In an ideal electricity market with perfect competition, the price formation should be governed by the short run marginal costs (SRMCs) [17, 98]. By ranking suppliers in the order of their SRMCs, a fundamental merit-order model can be established to simulate the electricity price. However, while taking into account the flexibility of power plants, the situation might change.

Recalling what we have analyzed in previous paragraphs, a flexibility-limited power plant can only vary its output within a certain range bounded by $\mathcal{E}_f^-(\cdot)$ and $\mathcal{E}_f^+(\cdot)$. Therefore, on a system level, if the overall residual load exceeds the aggregated upper flexible bound of those flexibility-limited resources, there will be fewer players left with spare capacity. In such a situation, those players will gain a strong bidding position to mark up the wholesale price [98]. Similarly, when the overall residual load goes below the aggregated lower flexible bound of those flexibility-limited resources, players with limited flexibility have to expect other players including RES generators to reduce/ curtail their production or consumers to raise their demand. In this case, those players would start to bid at a price that is lower than their SRMCs or even at negative prices in order to decrease other players' willingness to generate or consumers' willingness to consume.

In both of these two cases, the electricity price may depart significantly from the price derived from SRMCs. These effects have been studied by some researchers [98, 155–157]. Referring to the work by [98], we adopted exponential functions to model those effects. The determining variable is denoted as G_t^x/C_t^x, where x in the superscript denotes the class of generation in the merit order and C_t^x denotes the total available capacity of class x. The term G_t^x normally refers to the actual generation of class x, so higher G_t^x/C_t^x indicates relative supply shortage that will mark up the price and depart more significantly from SRMCs . However, in case when generation needs to be curtailed, G_t^x denotes the amount of generation that shall be curtailed, so higher G_t^x/C_t^x indicates relative supply surplus that will mark down the price and depart more significantly from SRMCs. Therefore, depending on which generation class that matches the residual load, the term G_t^x is calculated differently.

Denoting the residual load at time t as $\tilde{l}_t$ and combining Equation (4.11)-(4.14), we can first represent the class index x for merit order as:

$$x \in \begin{cases} \{\text{inflex.}\} & \tilde{l}_t \leq \tilde{C}_t^{\text{inflex.}} \\ \{\text{mid.}\} & \tilde{C}_t^{\text{inflex.}} \leq \tilde{l}_t \leq \tilde{C}_t^{\text{inflex.}} + \tilde{C}_t^{\text{mid.}} \\ \{\text{peak}\} & \tilde{C}_t^{\text{inflex.}} + \tilde{C}_t^{\text{mid.}} \leq \tilde{l}_t \leq \tilde{C}_t^{\text{total}} \end{cases} \tag{4.15}$$

And then G_t^x can be represented as:

$$G_t^x = \begin{cases} \tilde{C}_t^x - \tilde{l}_t & x \in \{\text{inflex.}\} \\ \tilde{l}_t - \tilde{C}_t^x & x \in \{\text{mid., peak}\} \end{cases} \tag{4.16}$$

While exponential regression are applied to model the two ends of merit-order curve where price may depart significantly from SRMCs, the middle of merit-order curve can be modeled with piece-wise linear regression [98]. Thereby, the merit-order model for price formation can be written as:

$$\tilde{\pi}_t = \begin{cases} a - b \cdot e^{-c\left(1-\frac{G_t^x}{C_t^x}\right)} & x \in \{\text{inflex.}\} \\ a + b \cdot \frac{G_t^x}{C_t^x} & x \in \{\text{mid.}\} \\ a + b \cdot e^{-c\left(1-\frac{G_t^x}{C_t^x}\right)} & x \in \{\text{peak}\} \end{cases} \tag{4.17}$$

where $\tilde{\pi}_t$ is price output of the merit-order curve, and a, b and c are non-negative values, i.e. $a, b, c \geq 0$. It shall be noticed that these terms a, b and c are placeholders for coefficients and are not necessarily identical between different classes. In fact, since we will use piece-wise functions for the middle class, a and b actually represent several sets of coefficients.

As mentioned previously, we first perform regressions using historical data to determine the coefficients in Equation (4.17).

SARIMA model

As discussed in Section 2.2.2, seasonal autoregressive integrated moving average (SARIMA) is commonly used for electricity price simulation. Given a time series of data y_t, a SARIMA model of order $(p, d, q) \times (P, D, Q)_s$ can be expressed by:

$$(1 - \sum_{k=1}^{p} \omega_k B^k)(1 - \sum_{k=1}^{P} \Omega_k (B^s)^k)(1 - B)^d (1 - B^s)^D y_t$$
$$= (1 - \sum_{k=1}^{q} \theta_k B^k)(1 - \sum_{k=1}^{Q} \Theta_k (B^s)^k)\epsilon_t$$

where, B is the backshift operator, ω_k are the autoregressive parameters, θ stand for the moving-average terms, Ω_k and Θ are the corresponding terms for season components, and ϵ_t are error terms which is usually assumed to be independent, identically distributed variables sampled from a normal distribution with zero mean.

Referring to a similar work [102], we apply a SARIMA of order $(2, 0, 2) \times (2, 0, 1)_s$ with seasonal AR(24), AR(168) and seasonal MA(168) to simulate the stochastic part of price $\dot{\pi}_t$, as following:

$$(1 - \omega_1 B - \omega_2 B^2)(1 - \Omega_{24}(B^s)^{24} - \Omega_{168}(B^s)^{168})\dot{\pi}_t$$
$$= (1 - \theta_1 B - \theta_2 B^2)(1 - \Theta_{168}(B^s)^{168})\epsilon_t$$

Summary

A high-level summary about the key information for market simulation model is provided as listed below:

Summary of market simulation module

Flexibility analysis on generation fleet:

Parameter:
Set of generation fleet by fuel type: $\mathbb{F}$
Envelop lines: $\mathcal{E}_f^+$, $\mathcal{E}_f^+$ $\quad \forall f \in \mathbb{F}$

Input:
Generation data: $g_{t,f} \quad \forall t \in \mathbb{T},\ \forall f \in \mathbb{F}' \subseteq \mathbb{F}$

Output:
Classified capacity by level of flexibility: $\tilde{C}_t^{\text{inflex.}}$, $\tilde{C}_t^{\text{mid.}}$, $\tilde{C}_t^{\text{peak}} \quad \forall t \in \mathbb{T}$
Total available capacity: $\tilde{C}_t^{\text{total}} \quad \forall t \in \mathbb{T}$

Merit-order model:

Parameter:
Coefficients for Equation (4.17): a, b, c

Input:
Residual load: $\tilde{l}_t \quad \forall t \in \mathbb{T}$
Outputs of ***flexibility analysis on generation fleet***

Output:
Simulated price: $\tilde{\pi}_t \quad \forall t \in \mathbb{T}$

SARIMA model:

Parameter:
SARIMA terms: ω_1, ω_2, Ω_{24}, Ω_{168}, θ_1, θ_2, Θ_{168}

Input:
None

Output:
Simulated price: $\dot{\pi}_t \quad \forall t \in \mathbb{T}$

Final simulated price:: $\pi = \tilde{\pi}_t + \dot{\pi}_t \quad \forall t \in \mathbb{T}$

4.2.3 Market constraints

The market constraints are a list of limits to make sure that the operation of a flexibility resource (determined by X in Equation (4.7)) would not violate the actual market rules and market conditions.

For all cases and in all marketplaces, the liquidity constraints shall always be fulfilled, i.e. the amounts of energy or capacity that players plan to trade shall never exceed the trading volumes in corresponding markets. Denoting the total volume of energy traded in energy marketplace i as $\hat{e}_{t,i}$ in MWh, and the total volume of capacity procured in ancillary service marketplace j as $\hat{c}_{t,j}$ in MW, the liquidity constraints are formulated as:

$$e^{+}_{t,i} \leq \hat{e}_{t,i} \; e^{-}_{t,i} \leq \hat{e}_{t,i} \; c_{t,j} \leq \hat{c}_{t,j}$$
$$\forall t \in \mathbb{T} = \{1, 2, \dots, T\} \; \forall i \in \mathbb{I} = \{1, 2, \dots, I\} \; \forall j \in \mathbb{J} = \{1, 2, \dots, J\}$$

Applying the same technique in Section 4.2.1 where decision variables are packaged in one vector X using Equation (4.7), we derive the vector form of trading volumes:

$$\hat{E}_i = \begin{bmatrix} \hat{e}_{1,i} \\ \hat{e}_{2,i} \\ \vdots \\ \hat{e}_{T,i} \end{bmatrix} \qquad \hat{C}_j = \begin{bmatrix} \hat{c}_{1,i} \\ \hat{c}_{2,i} \\ \vdots \\ \hat{c}_{T,i} \end{bmatrix}$$

$$\hat{E} = \begin{bmatrix} \hat{E}_1 \\ \vdots \\ \hat{E}_i \\ \vdots \\ \hat{E}_I \end{bmatrix} \qquad \hat{C} = \begin{bmatrix} \hat{C}_1 \\ \vdots \\ \hat{C}_i \\ \vdots \\ \hat{C}_I \end{bmatrix}$$

$$\hat{X} = \begin{bmatrix} \hat{E} \\ \hat{E} \\ \hat{C} \end{bmatrix} \tag{4.18}$$

Thereby, the vector form of liquidity constraint is formulated as:

$$\underbrace{\begin{bmatrix} \mathcal{I}_T \mid \mathcal{I}_T \mid \dots \mid \mathcal{I}_T \end{bmatrix}}_{(2I+J) \text{ times}} \cdot X \leq \hat{X} \tag{4.19}$$

where the element $\mathcal{I}_T$ is a T-order identity matrix[2], and it repeats $(2I + J)$ times along the latitudinal direction.

Besides the liquidity constraints, the other constraints are not applicable to all cases so have to be formulated on a case-specific base, especially some constraints that are resulted from market-specific rules. For example, offers in primary control reserve (PCR) market in Germany have to be made in

[2] A n-order identity matrix is a $n \times n$ square matrix with ones on the main diagonal and zeros elsewhere.

weekly blocks. In such a case, $c_{t,j}$ for $j \in \{\text{PCR}\}$ have to identical within the period of one week.

However, it is worth to emphasize one constraint that is applied only for arbitrage in day-ahead market. In day-ahead markets where the large volume of energy is traded, we limit the arbitrage behaviors so that they will not activate additional peak generation nor aggravate pressure on inflexible load when residual load is below the inflexible capacity. In those cases, arbitrageurs are making negative contributions to whole system flexibility. Such cases should be not possible in reality as price will respond to the arbitrageurs' behaviors, but they will possibly occur in the simulation with fixed price signal is taken as input. For instance, at a peak hour when electricity price is high, arbitrageurs would tend to sell as much energy as possible if the price maintains at that level. In such a case, energy provision by arbitrageurs may be excessive and become a negative factor for the whole system, similar to the case with excessive RES generation.

Therefore, combining the algorithm of flexibility analysis on generation fleet and its output, as introduced in Section 4.2.2, we implement an additional constraint to prevent such counterfactual activities to happen, which is formulated as:

$$e^{+}_{t,i} - e^{-}_{t,i} \leq \max\{0, l_{t,i} - \overline{C}^{\text{inflex.}}_{t} \cdot \Delta t\} \tag{4.20}$$

$$e^{-}_{t,i} - e^{+}_{t,i} \leq \max\{0, (\overline{C}^{\text{inflex.}} + \overline{C}^{\text{mid.}}_{t}) \cdot \Delta t - l_{t,i}\} \tag{4.21}$$

where, $i \in \{\text{day-ahead market}\}$ and Δt is the length of time step.

Taking Equation (4.20) as an example, it can be interpreted as: when residual load is higher than minimum generation level of inflexible power plants, the maximum volume can be traded by arbitrageur will $l_{t,i} - \overline{C}^{\text{inflex.}}_{t} \cdot \Delta$; otherwise if residual goes is already below minimum generation level of inflexible power plants, i.e. $l_{t,i} < \overline{C}^{\text{inflex.}}_{t} \cdot \Delta$, the constraint will be $e^{+}_{t,i} - e^{-}_{t,i} \leq 0$, i.e. arbitrageurs are not allow to inject more energy but are able to take excessive energy from the system.

Overall, there would be a list of market constraints depending on the actual market conditions and rules. These constraints can be generally formulated as:

$$\mathcal{M} \cdot X \leq \mathbf{M} \tag{4.22}$$

where, $\mathcal{M}$ is the coefficient matrix and $\mathbf{M}$ is the vector for limits of each market constraints. Taking the liquidity constraint as example:

$$\mathcal{M} = \underbrace{\left[\mathcal{I}_T \mid \mathcal{I}_T \mid \ \ldots \ \mid \mathcal{I}_T\right]}_{(2I+J)\ \text{times}}$$

$$\mathbf{M} = \hat{X}$$

Summary

A high-level summary about the key information for market constraint model is provided as listed below:

Summary of market constraint module

Taking liquidity constraint as an example

Decision variable: X

Input:
Trading volume in markets: $\hat{X}$

Output:
Constraint: $\mathcal{M} \cdot X \leq \mathbf{M}$

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, i.e. capital expenditures (CAPEX) 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.

For a energy storage system, the initial capital cost (denoted as $K^{\text{ini.}}$) 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) [110].

$$K^{\text{ini.}} = k^{\text{s}}\overline{s} + k^{\text{r}}\overline{r} \tag{4.23}$$

where, k^{s} and k^{s} are coefficients, in USD/MWh and USD/MW respectively. They 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 can be taken to build future scenarios, e.g. *ca.* 14% per annum according to [42].

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

$$K^{\text{EAC}} = K^{\text{ini.}} \cdot \frac{dr}{1 - \frac{1}{(1+dr)^a}} \tag{4.24}$$

where dr 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 ensuring our estimates of profitability for flexibility solutions are conservative.

The fixed O&M costs, K^{fOM} are added directly to the annualized capital cost to get the total fix costs (in USD/a):

$$K^{\text{fix}} = K^{\text{EAC}} + K^{\text{fOM}} \tag{4.25}$$

However, fixed O&M costs K^{fOM} are difficult to estimate precisely and are usually ignored in academic literature. Rastler *et al.* [66] estimated the fixed O& M cost as approximately 2% of the initial capital cost for energy storage systems. In this thesis, fixed O&M costs are neglected as well.

It shall be noted that, since K^{fix} is independent from operations, it makes no difference whether it is incorporated in the optimization or not. Therefore, we will only use it for final profitability analysis by comparing it to the operating profits derived from optimization using other modules.

For electric vehicle to grid (EV2G) and other types of demand response, the business model is different. Flexibility players are usually not responsible for costs of physical infrastructure. The operation-independent costs are mainly incurred by paying incentives (fees) for end-users for their participation [101]. Determination of such fees is via bilateral contract so is not a technical issue, usually not considered in academic literature [55,108]. Designing such business models are not within the scope of this study. Therefore, such costs are not considered. Nevertheless, the output of this study can still provide informative references for technology vendors by indicating the maximum market potential that could possibly realized.

Operation-dependent costs

Operation-dependent costs primarily refer to the degradation costs, which are specially an issue for battery-based energy storage systems [158].

However, as has been reviewed and analyzed in [110], there exists no single degradation model that is widely accepted in 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 state-of-charge (SoC)[3], degree-of-discharge (DoD) [4], charge/discharge rate, temperature, etc. [158]

- 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. [110]

Degradation costs can be neglected when 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 make 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 [110]. Nonetheless, it was also pointed out by [110] that while assuming degradation cost being zero, the operational planner would tend to operate the system more frequently, which would possibly in turn, violate the assumption of zero-degradation.

Such a combined investment and operation problem is hard to be incorporated in an optimization. Instead, a simplified linear relationship between the degradation and energy throughput is a common technique used in researches for estimating battery degradation [59] [62], which is also adopted in this study.

The operating lifetime of batteries is often given in in full-cycle equivalents (FCEs) that is the energy corresponding to a given number of full charge (or discharge). We denote the operating life time in FCE as α. Thereby, for a battery with energy capacity being $\overline{s}$ (in MWh), replacement costs being $K^{\text{rep.}}$ (in USD), and operating life time being α (in FCE), the linear degradation cost per energy throughput, denoted as ζ in USD/MWh, can be computed from the perspective of its whole life time:

$$\zeta = \frac{K^{\text{rep.}}}{\alpha \cdot \overline{s}}$$

With the unit degradation ζ, we can then calculate degradation cost as:

[3]State-of-charge is the equivalent of a fuel gauge for the battery pack, i.e. the ratio between the stored energy to the maximum energy capacity of the battery.

[4]Degree-of-discharge is the inverse of SoC, i.e. the ratio between how much energy has been consumed to the maximum energy capacity of the battery.

$$K^{\text{deg.}} = \sum_{t}^{t\in\mathbb{T}} K_t^{\text{deg.}} = \zeta \sum_{t}^{t\in\mathbb{T}} \left(\sum_{i}^{i\in\mathbb{I}} (e_{t,i}^{+} + e_{t,i}^{-}) + \sum_{j}^{j\in\mathbb{J}} (\delta_{t,j}^{+} + \delta_{t,j}^{-}) c_{t,j} \right) \tag{4.26}$$

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

$$\delta_{t,j}^{+} = \begin{cases} \delta_{t,j} & \delta_{t,j} \geq 0 \\ 0 & \delta_{t,j} < 0 \end{cases} \tag{4.27}$$

$$\delta_{t,j}^{-} = \begin{cases} 0 & \delta_{t,j} \geq 0 \\ -\delta_{t,j} & \delta_{t,j} < 0 \end{cases} \tag{4.28}$$

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 (4.26) 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 (4.8), we reconstruct the diagonal matrices with the decomposed ratios from Equation (4.27) and (4.28).

$$\Delta^{+} = diag(\delta_{1,1}^{+}, \delta_{2,1}^{+}, \ldots, \delta_{T,1}^{+}, \delta_{1,2}^{+}, \delta_{2,2}^{+}, \ldots, \delta_{T,2}^{+}, \ldots, \delta_{T,J}^{+}) \tag{4.29}$$

$$\Delta^{-} = diag(\delta_{1,1}^{-}, \delta_{2,1}^{-}, \ldots, \delta_{T,1}^{-}, \delta_{1,2}^{-}, \delta_{2,2}^{-}, \ldots, \delta_{T,2}^{-}, \ldots, \delta_{T,J}^{-}) \tag{4.30}$$

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

$$K^{\text{deg.}} = \mathcal{K} \cdot X \tag{4.31}$$

$$K^{\text{deg.}} = \begin{bmatrix} Z \mid & Z \mid & \zeta(\Delta^{+} + \Delta^{-}) \end{bmatrix} \begin{bmatrix} E^{+} \\ E^{-} \\ C \end{bmatrix}$$

where, X is the vector of decision variables referring to Equation (4.7), and Z is determined as following:

$$Z = \zeta \cdot \underbrace{\begin{bmatrix} \mathcal{I}_T \mid \mathcal{I}_T \mid \ \ldots \ \mid \mathcal{I}_T \end{bmatrix}}_{I \text{ times}}$$

where, the notation, "I times", indicates the element $\mathcal{I}_T$ repeats I times along the latitudinal direction, as introduced previously.

Summary

A high-level summary about the key information for market simulation model is provided as listed below:

Summary of cost module

Operation-independent cost:

Input:
Discount rate: dr
Designed life time: a
Cost coefficients: k^s, k^r
System capacity: $\overline{s}$ $\overline{r}$

Output:
Annualized fixed cost: K^{fix}

Operation-dependent cost:

Decision variable: X

Input:
Operating life time: α
Replacement cost: $K^{\text{rep.}}$
System capacity: $\overline{s}$
Frequency control signal: Δ^+, Δ^-

Output:
Coefficient matrix: $\mathcal{K}$

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 Systems (ESS)

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 charge, discharge and storage efficiency, denoted as η^c, η^d and η^s respectively.

Since the ramp up time for a small-to-medium storage system is typically within seconds [9] we consider it negligible comparing to the time resolution (1 or 0.5 hour) 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 (denoted as $\overline{s}$ that was introduced in Section 4.3.1). With a given initial state s_0, the state at each time step t can be determined using the equation below:

$$s_t = \eta^s s_{t-1} + \eta^c (\sum_i^{i \in \mathbb{I}} e^-_{t,i} + \sum_j^{j \in \mathbb{J}} \delta^-_{t,j} c_{t,j}) - \frac{1}{\eta^d} (\sum_i^{i \in \mathbb{I}} e^+_{t,i} + \sum_j^{j \in \mathbb{J}} \delta^+_{t,j} c_{t,j}) \tag{4.32}$$

In order to formulate Equation (4.32) into matrix form, we first make an illustration by assuming $\mathbb{I} = \{1\}$, which means trading is performed in only one energy marketplace. Then Equation (4.32) becomes:

$$s_t = s_{t-1} + \eta^c e^-_{t,1} - \frac{1}{\eta^d} e^+_{t,1} \tag{4.33}$$

The formulation of this equation at time steps is listed below:

$$\begin{cases} s_0 = s_0 & t = 0 \\ s_1 = \eta^s s_0 + \eta^c e^-_{1,1} - \frac{1}{\eta^d} e^+_{1,1} & t = 1 \\ s_2 = \eta^s \left(\eta^s s_0 + \eta^c e^-_{1,1} - \frac{1}{\eta^d} e^+_{1,1} \right) + \eta^c e^-_{2,1} - \frac{1}{\eta^d} e^+_{2,1} & t = 2 \\ s_3 = \eta^s \left(\eta^s \left(\eta^s s_0 + \eta^c e^-_{1,1} - \frac{1}{\eta^d} e^+_{1,1} \right) + \eta^c e^-_{2,1} - \frac{1}{\eta^d} e^+_{2,1} \right) + \eta^c e^-_{3,1} - \frac{1}{\eta^d} e^+_{3,1} & t = 3 \\ \vdots & \\ s_T = (\eta^s)^T s_0 + \eta^c \left[(\eta^s)^{T-1} e^-_{T,1} + (\eta^s)^{T-2} e^-_{T-1,1} + \dots \right] & \\ & t = T \\ \qquad - \frac{1}{\eta^d} \left[(\eta^s)^{T-1} e^+_{T,1} + (\eta^s)^{T-2} e^+_{T-1,1} + \dots \right] & \end{cases}$$

Therefore, Equation (4.33) can be formulated in matrix form as:

$$S = H^s S_0 + \eta^c H E^-_1 - \frac{1}{\eta^d} H E^+_1$$

where, E^-_1 and E^+_1 are derived by Equation (4.5), and:

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

$$S_0 = \underbrace{\begin{bmatrix} s_0 & s_0 & \dots & s_0 \end{bmatrix}}_{T \text{ times}}^T$$

$$H^s = diag((\eta^s)^1, (\eta^s)^2, \dots, (\eta^s)^T)$$

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

In order to extending this approach to more general cases where multiple elements may exist in $\mathbb{I}$ and $\mathbb{J}$, we construct H_I and H_J based on H:

$$H_I = \underbrace{\begin{bmatrix} H \mid H \mid \dots \mid H \end{bmatrix}}_{I \text{ times}}$$

$$H_J = \underbrace{\begin{bmatrix} H \mid H \mid \dots \mid H \end{bmatrix}}_{J \text{ times}}$$

In this way, the matrix form of Equation (4.32) can be derived as:

$$S = H^s S_0 + \left[-\tfrac{1}{\eta^d} H_I \;\mid\; \eta^c H_I \;\mid\; H_J(-\tfrac{1}{\eta^d}\Delta^+ + \eta^c \Delta^-) \right] \cdot X \tag{4.34}$$

where, Δ^+ and Δ^- are given by Equation (4.29) and (4.30), the vector for decision variables X is formulated by Equation (4.7).

In order to make it more compact, we reformulate Equation (4.34) as:

$$S = \mathcal{H}_0 + \mathcal{H} \cdot X \tag{4.35}$$

where

$$\mathcal{H}_0 = H^s S_0 \tag{4.36}$$

$$\mathcal{H} = \left[-\tfrac{1}{\eta^d} H_I \;\mid\; \eta^c H_I \;\mid\; H_J(-\tfrac{1}{\eta^d}\Delta^+ + \eta^c \Delta^-) \right] \tag{4.37}$$

Electric Vehicle to Grid (EV2G)

In this thesis, EV2G is taken as an example of load-shifting (demand response) applications. Although the function of EV2G systems is fundamentally battery-like, flexibility provision from EV2G on a system level are closer to other types of load-shifting technologies considering the following characteristics:

- The availability of resources is dynamic and determined by end-users' behaviors.

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

- Energy will be consumed for their purposes by end-users rather than be utilized exclusively to deliver services to the grid.

  For EV2G systems, energy will be consumed for drivings of EVs.

While the second point will only impact on the result, tackling the first one requires modifications on the model. In order to take into account the users' behavior, we add some additional features on top of the storage model, by conceiving the whole EV2G system as a dynamic storage system[5].

In order to transform the storage model 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. These terms are correlated as:

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

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:

$$\begin{aligned} s_t =& \eta^s s_{t-1} + s_t^+ n_t^+ - s_t^- n_t^- \\ &+ \eta^c \left(\sum_i^{i\in\mathbb{I}} e_{t,i}^- + \sum_j^{j\in\mathbb{J}} \delta_{t,j}^- c_{t,j} \right) - \frac{1}{\eta^d} \left(\sum_i^{i\in\mathbb{I}} e_{t,i}^+ + \sum_j^{j\in\mathbb{J}} \delta_{t,j}^+ c_{t,j} \right) \end{aligned} \tag{4.39}$$

Equation (4.38) can be written in matrix format as:

$$N = \mathcal{I}_T N_0 + \mathcal{L}_T N^+ - \mathcal{L}_T N^- \tag{4.40}$$

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

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

$$N_0 = \underbrace{\begin{bmatrix} n_0 & n_0 & \dots & n_0 \end{bmatrix}}_{T \text{ times}}^T$$

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

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

[5]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 considered to be out of the scope.

$$S^+ = diag(s_1^+, s_2^+, \dots, s_T^+)$$
$$S^- = diag(s_1^-, s_2^-, \dots, s_T^-)$$

Following the same procedure and using the same notations made for storage system, Equation (4.39) can be expressed in matrix form as:

$$\begin{aligned} S = {} & H^s S_0 + HS^+N^+ - HS^-N^- \\ & + \left[-\tfrac{1}{\eta^d} H_I \;\mid\; \eta^c H_I \;\mid\; H_J(-\tfrac{1}{\eta^d}\Delta^+ + \eta^c \Delta^-) \right] X \end{aligned} \tag{4.41}$$

which can be reformulated as:

$$S = \mathcal{H}_0 + \mathcal{H} \cdot X \tag{4.42}$$

where

$$\mathcal{H}_0 = H^s S_0 + HS^+N^+ - HS^-N^- \tag{4.43}$$

$$\mathcal{H} = \left[-\tfrac{1}{\eta^d} H_I \;\mid\; \eta^c H_I \;\mid\; H_J(-\tfrac{1}{\eta^d}\Delta^+ + \eta^c \Delta^-) \right] \tag{4.44}$$

Summary

A high-level summary about the key information for market simulation model is provided as listed below:

Summary of technology simulation module

Energy storage system:

Parameters:
Battery efficiencies: η_c, η_d, η_s

Input:
Initial state: s_0
Frequency control signals: Δ_+, Δ_-
Selected marketplaces: $\mathbb{I}$, $\mathbb{J}$
Output:
Coefficient matrices: $\mathcal{H}$, $\mathcal{H}_0$

(Continued on next page)

Summary of technology simulation module (continued)

Electric vehicle to grid system:

Parameters:
Battery efficiencies: η_c, η_d, η_s
Electric vehicle driving profile: N, N_0,N^+,N^-

Input:
Initial state: s_0
Frequency control signals: Δ_+, Δ_-
Selected marketplaces: $\mathbb{I}$, $\mathbb{J}$
Output:
Coefficient matrices: $\mathcal{H}$, $\mathcal{H}_0$

4.3.3 Technology constraints

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

Energy storage

Firstly, maximum (dis)charge rate, $\overline{r}$ (assuming symmetric for charge and discharge), shall able to fulfill needs of offering energy and capacity in all marketplaces:

$$0 \leq \frac{1}{\Delta t} \sum_{i}^{i \in \mathbb{I}} e^+_{t,i} + \sum_{j}^{j \in \mathbb{J}} c_{t,j} \leq \overline{r} \quad \forall t \in \mathbb{T}$$

$$0 \leq \frac{1}{\Delta t} \sum_{i}^{i \in \mathbb{I}} e^-_{t,i} + \sum_{j}^{j \in \mathbb{J}} c_{t,j} \leq \overline{r} \quad \forall t \in \mathbb{T}$$

It can be noticed that opposite movement of charge/ discharge 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 bounded between 0 and maximum capacity, $\overline{s}$:

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

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

$$0 \leq \eta^s s_{t-1} + \eta^c \left(\sum_i^{i \in \mathbb{I}} e^-_{t,i} + \sum_j^{j \in \mathbb{J}} \delta^-_{t,j} c_{t,j} \right) - \frac{1}{\eta^d} \left(\sum_i^{i \in \mathbb{I}} e^+_{t,i} + \sum_j^{j \in \mathbb{J}} \delta^+_{t,j} c_{t,j} \right) \leq \overline{s}$$

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

$$-\left[\left(\tfrac{1}{\Delta t} \cdot \mathcal{I}_I \right) \mid \left(\tfrac{1}{\Delta t} \cdot \mathcal{O}_I \right) \mid \mathcal{I}_J \right] X \leq 0 \tag{4.45}$$

$$-\left[\left(\tfrac{1}{\Delta t} \cdot \mathcal{O}_I \right) \mid \left(\tfrac{1}{\Delta t} \cdot \mathcal{I}_I \right) \mid \mathcal{I}_J \right] X \leq 0 \tag{4.46}$$

$$\left[\left(\tfrac{1}{\Delta t} \cdot \mathcal{I}_I \right) \mid \left(\tfrac{1}{\Delta t} \cdot \mathcal{O}_I \right) \mid \mathcal{I}_J \right] X \leq \overline{R} \tag{4.47}$$

$$\left[\left(\tfrac{1}{\Delta t} \cdot \mathcal{O}_I \right) \mid \left(\tfrac{1}{\Delta t} \cdot \mathcal{I}_I \right) \mid \mathcal{I}_J \right] X \leq \overline{R} \tag{4.48}$$

where,

$$\overline{R} = \underbrace{\begin{bmatrix} \overline{r} & \overline{r} & \dots & \overline{r} \end{bmatrix}}_{T \text{ times}}^T$$

and

$$\mathcal{I}_I = \underbrace{\left[\mathcal{I}_T \mid \mathcal{I}_T \mid \dots \mid \mathcal{I}_T \right]}_{I \text{ times}}$$

$$\mathcal{I}_J = \underbrace{\left[\mathcal{I}_T \mid \mathcal{I}_T \mid \dots \mid \mathcal{I}_T \right]}_{J \text{ times}}$$

$$\mathcal{O}_I = \underbrace{\left[\mathcal{O}_T \mid \mathcal{O}_T \mid \dots \mid \mathcal{I}_T \right]}_{I \text{ times}}$$

where, $\mathcal{O}_T$ is a $T \times T$ zero matrix.

Inheriting the notations of $\mathcal{H}$ and $\mathcal{H}_0$ that are introduced by Equation (4.35) to (4.37), the constraints of storage are formulated as:

$$-\mathcal{H} \cdot X \leq \mathcal{H}_0 \tag{4.49}$$

$$\mathcal{H} \cdot X \leq \overline{S} - \mathcal{H}_0 \tag{4.50}$$

where,

$$\overline{S} = \underbrace{\begin{bmatrix} \overline{s} & \overline{s} & \dots & \overline{s} \end{bmatrix}}_{T \text{ times}}^T$$

Electric vehicle to grid

The constraints for ESS are generally portable for the EV2G systems, by simply re-using Equation (4.42) to (4.44) to derive $\mathcal{H}$ and $\mathcal{H}_0$, and replacing the upper bound limit in Equation (4.47) with

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

where, N is determined by Equation (4.40).

Summary

Similar to the market constraints, the form of all technology constraints can be generalized and expressed as:

$$\mathcal{T} \cdot X \leq \mathbf{T} \tag{4.52}$$

where, $\mathcal{T}$ is the coefficient matrix and $\mathbf{T}$ is the vector for limits of each market constraints. Taking the constraint given by Equation (4.50) as example:

$$\mathcal{T} = \mathcal{H}$$

$$\mathbf{T} = \overline{S} - \mathcal{H}_0$$

A high-level summary about the key information for market simulation model is provided as listed below:

Summary of technology constraint module

Decision variable: X

Input:
Outputs of **Technology Simulation module**
System capacity: $\overline{s}$, $\overline{r}$
Additional for EV2G - EV driving profiles: N

Output:
A set of constraints in the form of: $\mathcal{T} \cdot X \leq \mathbf{T}$

4.4 Optimization Engine

The performance of a flexibility resource depends primarily on the operation plan, which is represented as X given by Equation (4.7). 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 the market calculated with the results from optimization gives the upper bound of the market value.

Using the outputs of all the modules discussed above, we can formulate the optimization problem as:

$$\max_{X} (\mathcal{R} - \mathcal{K}) \cdot X$$

subject to:

$$\mathcal{M} \cdot X \leq \mathbf{M}$$
$$\mathcal{T} \cdot X \leq \mathbf{T}$$

where, $\mathcal{R}$ comes from the revenue module (Section 4.2.1), $\mathcal{K}$ is obtained by cost module (Section 4.3.1), $\mathcal{M} \cdot X \leq \mathbf{M}$ represents a set of market constraints derived from market constraint module (Section 4.2.3), and $\mathcal{T} \cdot X \leq \mathbf{T}$ represents a set of technology constraints derived from technology constraint module (Section 4.3.3).

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

4.5 Valuation metrics

After the optimal operating plan, X^*, is obtained, we can re-calculate the revenue and cost separately and analyze the results in a certain metric. The metric to evaluate the system performance are slightly different between ESS and EV2G. For ESS, the criteria in the evaluation metric include:

- **Revenue:** the total explicit revenue from electricity markets calculated as Equation (4.3) in Section 4.2.1, per annum:

$$R = \mathcal{R} \cdot X^*$$

- **Operating cost:** the operation-dependent costs (essentially degradation cost); refer to Section 4.3.1 and Equation (4.26), per annum:

$$K^{\text{deg.}} = \mathcal{K} \cdot X^*$$

- **Operating Profit**: the total revenue net of the operating cost, per annum, denoted as $P^{\text{op.}}$. This is also the value of the objective function of our optimization:

$$P^{\text{op.}} = (\mathcal{R} - \mathcal{K}) \cdot X^*$$

- **Fixed cost:** K^{fix}, that is independent with operating plan X and is calculated referring to Section 4.3.1.
- **Profit:** the total revenue net of both operation-dependent and fixed costs, per annum, i.e. net profit, denoted as P^{net}:

$$P^{\text{net}} = P^{\text{op.}} - K^{\text{fix}}$$

- **Profitability ratio**: the ratio between the profit and overall costs including both operating and fix costs, denoted as ρ:

$$\rho = \frac{P^{\text{net}}}{\mathcal{K} \cdot X^* + K^{\text{fix}}}$$

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 (4.3), per annum:

$$R = \mathcal{R} \cdot X^*$$

- **Operating cost:** the operation-dependent costs (essentially degradation cost), per annum:

$$K^{\text{deg.}} = \mathcal{K} \cdot X^*$$

- **Implicit Charging Cost**: the cost of energy compensation for EV driving demands. This part of cost has been implicitly deduced from the revenue, denoted as $K^{\text{imp.}}$. However, in order to better understand the system dynamic and provide more reference for business planning, we re-calculated by multiplying the total energy consumption with volume-based average price in real time π^*, per annum:

$$K^{\text{imp.}} = \pi^* \cdot \left[(-\mathcal{I}_T) \overset{\times I}{\cdots\cdots} \;\middle|\; (\mathcal{I}_T) \overset{\times I}{\cdots\cdots} \;\middle|\; -\Delta^+ + \Delta^- \right] X^*$$

- **Profit:**: revenue net of costs including operating cost only since the investments on technology are made to be zero as is discussed at the beginning of this section, per annum:

$$P^{\text{net}} = (\mathcal{R} - \mathcal{K}) \cdot X^*$$

- **Profitability ratio**: the ratio between the profit and overall costs including both operating and implicit charging costs

$$\rho = \frac{P^{\text{net}}}{\mathcal{K} \cdot X^{*} + K^{\text{imp.}}}$$

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 should be raised when comparisons between these two technologies are made using the approach of this thesis.

4.6 Additional measures for special cases

4.6.1 Back-casting technique for sensitivity analysis

As has been discussed in Section 2.2.2, we will follow the common approach adopted by much of the research that first assign perfect foresight of future price movements to players and conducted sensitivity analysis using back-casting technique. Values obtained with the perfect price foresight indicates the upper bound of market values. On the contrary, back-casting technique is the simplest and naivest method to forecast leads to an estimation of lowest possible values. In reality, players will be able to apply some advanced forecasting methods and the actual value captured shall be between the upper and lower bounds.

The primitive back-casting method we used is assuming the players will predict the future price, using historical price lags for a period of time, τ. Typically, τ could be the length of one day or one week. Taking energy price as example, the mathematical formulation of the primitive back-casting method is listed below:

$$\hat{\pi}_t = \pi_{t-\tau}$$

where, $\hat{\pi}_t$ is the predicted future price at time t and $\pi_{t-\tau}$ is the actual historical price at $t - \tau$. The placeholder π is interchangeable with other price terms, ϕ and ψ.

4.6.2 Coupling day-ahead and real-time energy market

When we value a case where the market player player can participate in day-ahead and real-time (intra-day, balancing) energy markets at the same time, an issue arises 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 benefits from unrealistic foresight, it has to be constrained. Some researchers have also noticed this issue and used techniques such as putting a proportional constraint of real-time volume to day-ahead volume [106] or deny reserved biddings between day-ahead and real-time market [62].

In this thesis, the virtual arbitrage has already been damped by the technology degradation model as has been discussed in Section 4.3.1 and restricted by the rate constraints in Section 4.3.3. In this way, although some arbitrage transactions do not physically activate the flexibility resources, they are conceived to incur operational costs and are always complied with the technology constraints. Therefore, the risk- and cost- free virtual arbitrage is eliminated in our study.

4.6.3 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 [110] [159] [160] [161] 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.

4.7 Summary

Chapter 5

Case Studies

This chapter presents the results of three selected cases. We first apply the analytical frameworks established in Chapter 3 to characterize the market regimes in three cases and identify potential business opportunities for flexibility solutions. Thereafter, the quantitative methodology developed in Chapter 4 is used to estimate the market potential and profitability of selected flexibility solutions. It was found

5.1 Case selection: rationale and definition

The goal of this thesis is to provide technology vendors, especially those who have an international ambition, a reference for strategic business planning regarding electricity flexibility solutions in different power market jurisdictions. This defines our rationale for case selections, explained below.

First, the case studies should be carried out in markets that have an significant impact on business on a global scale, so that results from case studies can be direct references to help technology vendors establish a global view of the business landscape for flexibility solutions. Therefore, we determine three targeted countries as the Unite States, Germany and Australia, which are major economies in North America, Europe and Asia-Pacific respectively.

Second, each case shall refer to an independent and integral power market jurisdiction. Based on our defined scope, the cases should be mature liberalized power markets with all necessary market components to manage and organize essential functions for power system operations. For this reason, the US and Australia are broken up to several market regimes and those that are managed by vertically integrated and regulated entities are exclude.

Besides, power market structures should be heterogeneous so that the major structural attributes discussed in Chapter 3 can be compared and illustrated.

Finally, considering research feasibility, there shall be abundant literature and reliable data sources for the cases to be studied.

Based on these considerations we define three cases, i.e. the PJM Interconnection power market, the power market in Germany, and New South Wales pricing zone in Australia's National Electricity Market. They will be referred to as **PJM**, **DE** and **NSW**, respectively in the reminder of this thesis. Their definitions and general information are introduced as following.

Case 1: PJM

The first case refers to the energy, capacity and ancillary service markets managed and organized by PJM Interconnection LLC.

PJM Interconnection LLC.[1] is a independent system operator (ISO) that operates a competitive wholesale electricity market and manages the high-voltage electricity grid in all or parts of Delaware, Illinois, Indiana, Kentucky, Maryland, Michigan, New Jersey, North Carolina, Ohio, Pennsylvania, Tennessee, Virginia, West Virginia and the District of Columbia. Therefore, PJM Interconnection has the dual role of being both a market operator (MO) and a transmission system operator (TSO). The geographic coverage is illustrated in Figure 5.1.

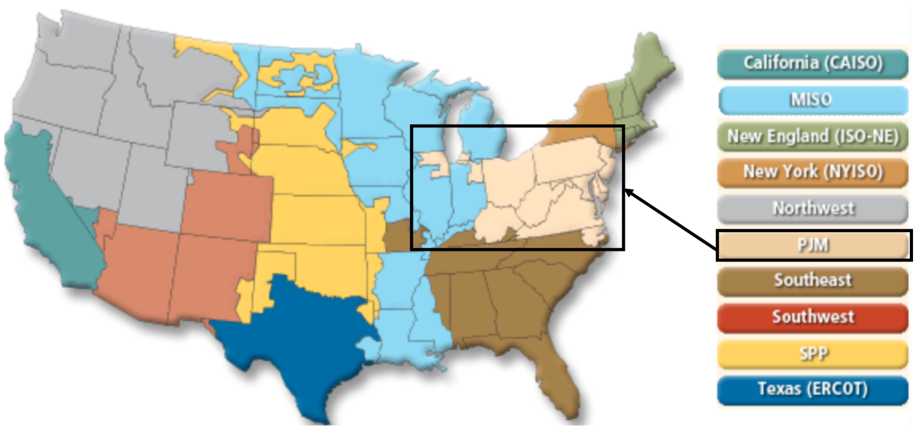

Figure 5.1: The geographic coverage of electricity markets in the US [162]

PJM is regulated by the Federal Energy Regulatory Commission (FERC). Leading utility companies in PJM power markets including: Commonwealth Edison, American Electric Power (AEP), Pennsylvania Power & Light (PP&L), etc.

[1]PJM originally stands for "Pennsylvania-New Jersey-Maryland area". Although that name is sometimes referred to in the literature, it has been never seen in official documents published in recent years by PJM and its regulator FERC.

Case 2: DE

The second case refers to the power markets in Germany. The definition is less straightforward compared to the first case, since market organizations are unbundled from the physical systems.

First of all, we define the physical system as physical activities of power systems including generation, transmission & distribution, and consumption in the territories of 4 TSOs, i.e. TenneT, 50Hertz, Amprion and TransnetBW, which operate the power grids covering the whole geography of Germany, illustrated by Figure 5.2.

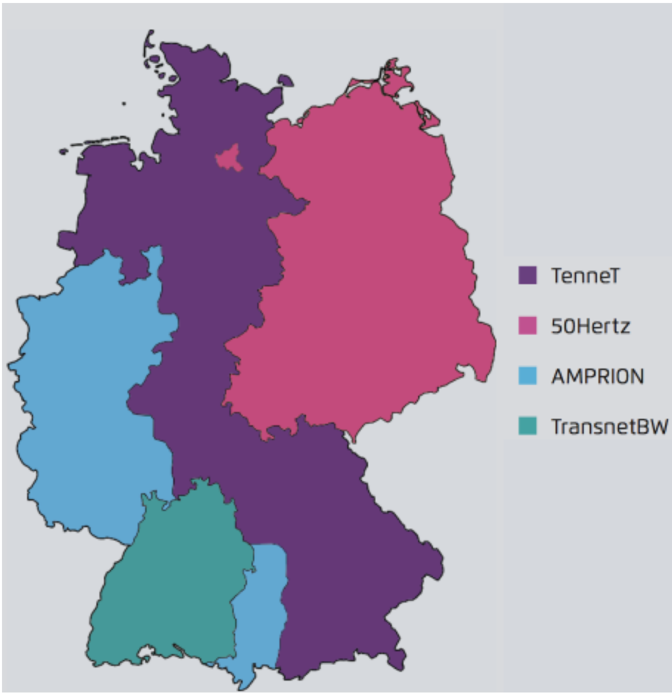

Figure 5.2: The geographic coverage of 4 TSOs in Germany [163]

On the market aspect, the electricity market is fully liberalized and transactions can be made either through bilateral agreements over the counter (OTC) or through centralized power exchange. The major power exchanges are the European Energy Exchange (EEX) in Leipzig for forward products and the EPEX SPOT in Paris for spot trading. EPEX SPOT organizes a day-ahead market and an intra-day market. Territories of TSOs in Germany and Austria are coupled in a single bidding zone in the day-ahead market. Increasing proportion of electricity transactions is observed to made through EPEX SPOT [163]. In 2016, the trading volume in the Germany/ Austria day-ahead market of EPEX SPOT was equal to over 45% of the total electricity demands in Germany[2].

[2] Own calculation based data described in Appendix A

Ancillary services in Germany are responsible by the 4 TSOs and coordinated by German grid control cooperation (in German Netzregelverbund, NRV). NRV was established by the German TSOs in 2012 and since it was founded, market activities for ancillary services among 4 TSOs have been unified. More details will be discussed in next section.

There is no capacity market existing in Germany.

The regulator for electricity sector is the Federal Network Agency (in German Bundesnetzagentur, BNetzA) and major utility companies include RWE, E.ON, EnBW, and Vattenfall, often referred to as the "big 4".

Case 3: NSW

Case 3 refers to the pricing zone of New South Wales in Australia's National Electricity Market operated by Australia Energy Market Operator (AEMO) who is both the market operator (MO) and system operator (SO) in Australia.

Figure 5.3: The geographic coverage and pricing zones of Australia's National Electricity Market [163]

AEMO manages the National Electricity Market (NEM) for the power system in Australia's eastern and south-eastern seaboard, and Wholesale Electricity Market (WEM) for the power system in Western Australia. Within NEM, zonal pricing scheme is applied and market price is settled based on the Regional Reference Price (RRP) for five RRP zone areas: Queensland, New South Wales, Victoria, South Australia and Tasmania [139, 164], as illustrated by Figure 5.3.

Besides, AEMO operates separate markets for the delivery of ancillary services, which are also settlement separately in the five RRP zones.

Among these zones, NSW is selected since it is the largest segment in terms of aggregated trading volume [164].

AEMO is governed by the Australian Energy Market Commission (AEMC) that is responsible for developing and making rules, and is regulated by the Australian Energy Regulator (AER) [164]. Key utility companies in New South Wales include Origin Energy, Energy Australia and AGL.

Indication of general market scale

Table 5.1 lists the key statistics that characterize physical properties of three cases. It should be able to provide readers an intuitive comparison of the general scale between different cases. Moreover, some numbers will be used as metrics in quantiative studies to be discussed in Section 5.3.

Table 5.1: Key statistics for comparison of scale across three cases

Item	**PJM**	**DE**	**NSW**
Population covered (million)	65.0	82.7	7.5
Metering point (million)	30.3	51.9	3.4
Generation capacity (MW, 2016)	176 569	200 888	16 319
Consumption (2016)			
Average rate, in MW	87 793	59 138	7978
Aggregated volume, in TWh	771.2	519.5	70.1

From Table 5.1, we can notice that PJM and DE are roughly on the same scale while NSW is one order of magnitude smaller than the other two.

5.2 Qualitative assessment on market regimes and business opportunities

In this section, we first apply the analytical framework established in Chapter 3 to characterize and compare the market regimes in three cases, followed by detailed analysis of each case, based on which we identify potential business opportunities for flexibility solutions in those three regions.

Table 5.2 presents a high level comparative description of the market design in three cases.

It can be seen that market structures are indeed diverse among the three cases. Overall, PJM offers the most comprehensive routines for participation of flexibility solutions. Through its specially designed “Demand Response” program, all kinds of behind-the-meter flexibility solutions can participate in all segments of its power markets, including energy, capacity and ancillary

Table 5.2: Comparison of power market regimes in three cases

Characteristic	**PJM**	**DE**	**NSW**
Energy market			
Power pool (PP) or power exchange (PX)	PP	PX	PP
Demand-side participation	Yes	Yes	In process
Marketplace	Day-ahead Real-time	Day-ahead Intra-day Balancing	Real-time
Pricing scheme	Nodal pricing	Zonal pricing	Zonal pricing
Frequency control ancillary service market			
Marketplace			
Primary control	*No market*	Primary control	*No market*
Secondary control	Regulation RegD, Regulation RegA	Secondary control	Regulation Lower, Regulation Raise
Tertiary control	Synchronous, Non-synchronous, Supplementary	Tertiary control	Contingency Lower (Fast, Slow, Delayed), Contingency Raise (Fast, Slow, Delayed)
Demand-side participation	Yes	No	Yes
Market model	Decentralize	Centralize	Centralized
Capacity remuneration mechanism			
Capacity market	Yes	Energy-only	Energy-only
Other remuneration mechanism		Interruptible loads	Emergency DR
Demand-side participation	Yes	Yes	Piloting

service markets [68]. In NSW, AEMO is proactively innovating its market designs aiming at more incentives for flexibility solutions, although many of the implementations are still at pilot stage. In DE, hurdles against emerging flexibility solutions mainly exist in the ancillary service market, while its fully liberalized energy market is theoretically non-discriminatory to all technologies. More details are providing in the reminder of this section.

PJM

PJM Energy and frequency control market
Demand
Germany
AEMO

5.2.1 Analysis of power market structure in selected jurisdictions

5.2.2 Identified business opportunities in selected jurisdictions

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)

- **PJM Interconnection**
  - **Abbreviation**: PJM
  - **TSO**: PJM ISO
  - **MO**: PJM ISO
  - **Regulator**: FERC
  - **Geographic coverage**: All or parts of Delaware, Illinois, Indiana, Kentucky, Maryland, Michigan, New Jersey, North Carolina, Ohio, Pennsylvania, Tennessee, Virginia, West Virginia and the District of Columbia.
- **Germany**
  - **Abbreviation**: DE
  - **TSO**: 4 TSOs
  - **MO**: EPEX SPOT for centralized wholesale spot power exchange, ENTSO-E for primary frequency control market, TSOs coordinated by BNG
  - **Regulator**: BNG
  - **Geographic coverage**: Germany[3]

[3]EPEX Germany/Austria

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:

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

5.2.3 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" [129]. 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. [129] [146] 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 $i \in \{RegD\}$.

5.2.4 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.

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

5.2.5 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.

5.3 Quantitative studies and results on market size and profitability

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.

5.3.1 Data, parameters and scenarios

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 5.2, 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) [168], 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 [169]. 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 5.3.

Table 5.3: Parameters for cost calculation

Items	**Unit**	**Value**
Energy cost coefficient, C^s	$\$/kWh$	350
Power cost coefficient, C^r	$\$/kW$	0
Technology cost, 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.

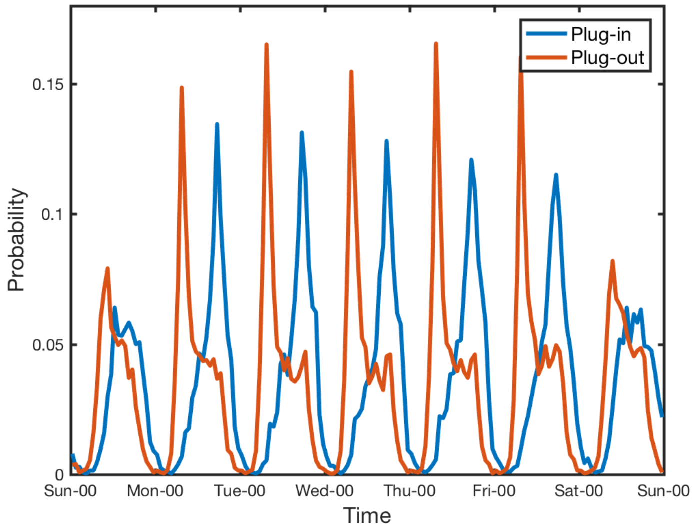

Figure 5.4: Probability of EV plug-in/ plug-out

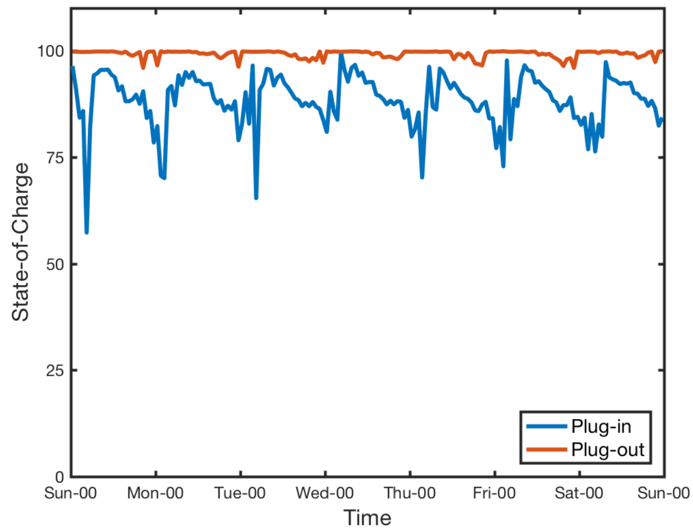

Figure 5.5: Average SoC of EV when plug-in/ plug-out

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 [170] 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 [171].

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 [172]. 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 5.4-5.5 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 (4.3) in Section 4.2.1, per annum

- **Operating cost:** the operation-dependent costs (essentially degradation cost); refer to Section 4.3.1 and Equation (4.26), 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 (4.3), 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 5.6 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**".

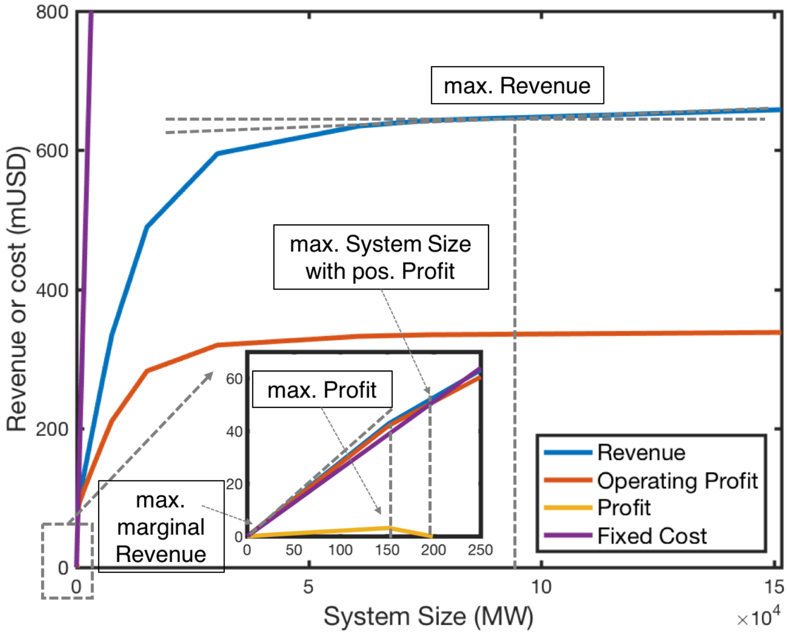

Figure 5.6: Graphic illustration of 4 scenarios

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 5.4: 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 ($\mathrm{USD}/(\mathrm{a} \cdot \mathrm{MW})$). 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 [173] [174] [175]. All the relevant numbers are listed in Table 5.4.

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 [176].

5.3.2 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

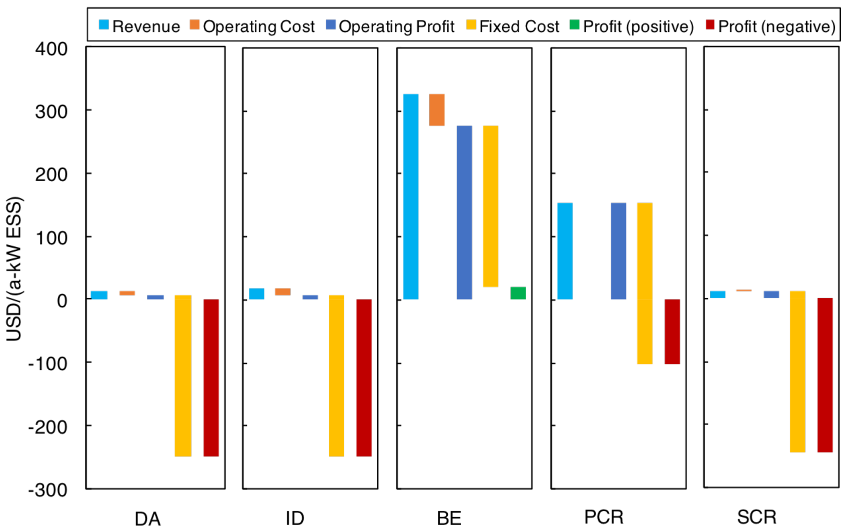

Figure 5.7: Profitability of ESS in Germany electricity markets in the scenario of "max. marginal Revenue"

As is discussed, profitability analysis can be performed using the scenario "max. marginal Revenue", the results of which are depicted by Figure 5.7. 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 5.8, 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

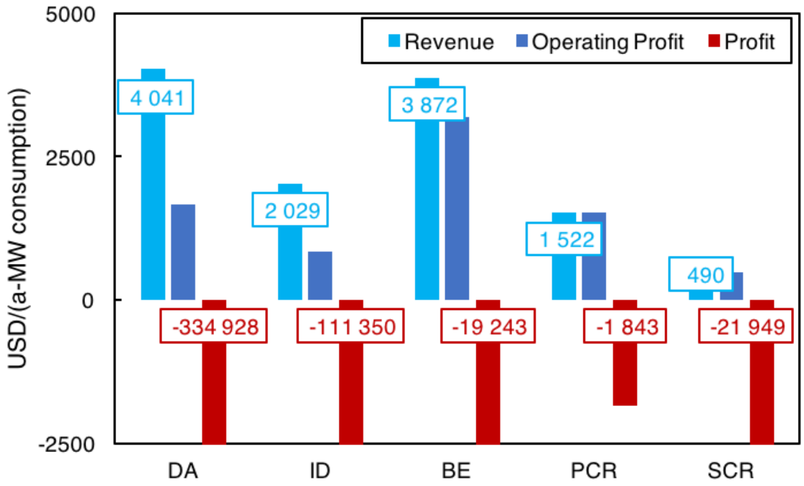

Figure 5.8: Market size of ESS in Germany electricity markets in the scenario of “max. Revenue”

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 5.2, 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 5.9.

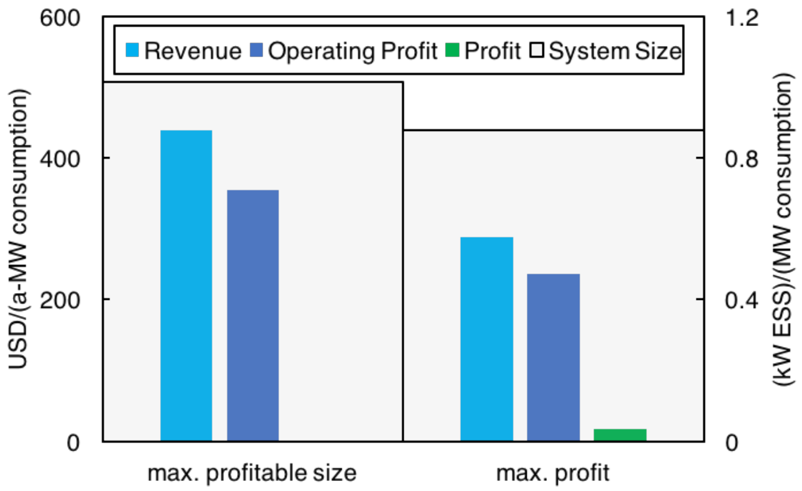

Figure 5.9: Market size of ESS in Germany electricity markets in the scenario of “max. System size with pos. Profit” and “max. Profit”

It can be seen from Figure 5.9, 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 5.2. 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 5.7.

On the other hand, we noticed from Figure 5.7 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 5.2. Theoretically, players shall get higher turnover in the frequency control markets than avoided balancing energy charges. Furthermore, the actual total payment for SCR in Germany is 176 mUSD in 2016 which is equavilent to 2976 USD/$(\mathrm{a} \cdot \mathrm{MW})$, while the maximum achievable revenue with BESSs are bounded at 490 USD/$(\mathrm{a} \cdot \mathrm{MW})$ as shown in Figure 5.8 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 5.2. 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 [110], 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 5.8. Even in the scenario of maximum unit return, the losses are about 10-20 times of the revenue; see Figure 5.7. 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.

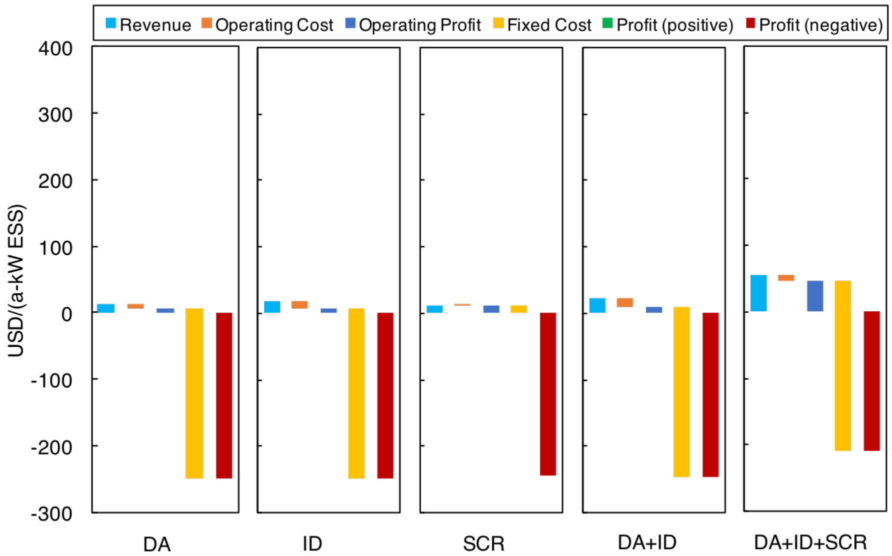

Figure 5.10: Profitability of ESS with multitasking in Germany electricity markets

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 5.11 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,

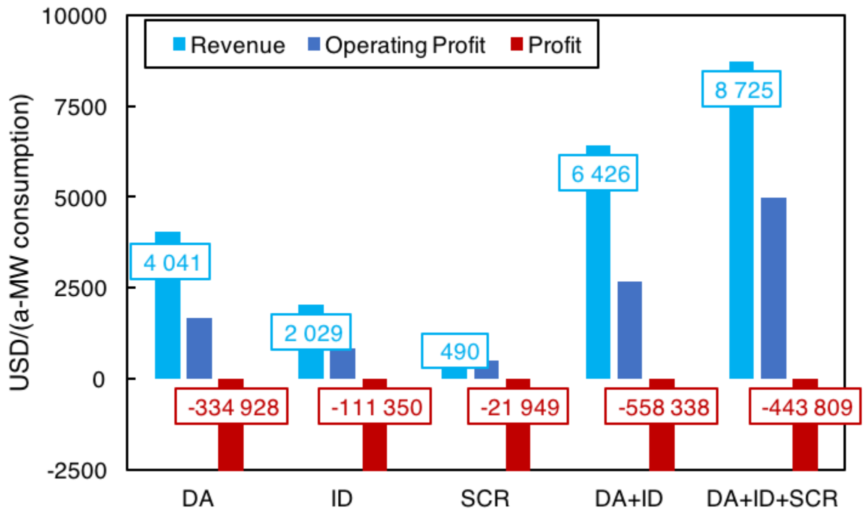

Figure 5.11: Market size of ESS with multitasking in Germany electricity markets

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 5.12 and Figure 5.13.

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

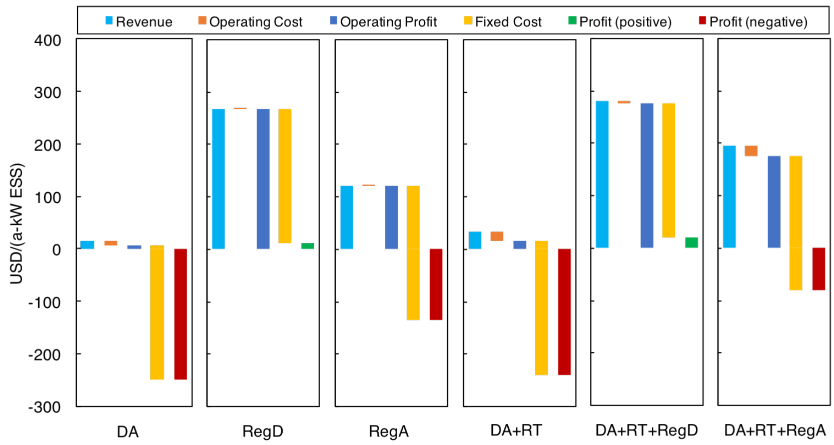

Figure 5.12: Profitability of ESS in PJM electricity markets in the scenario of "max. marginal Revenue"

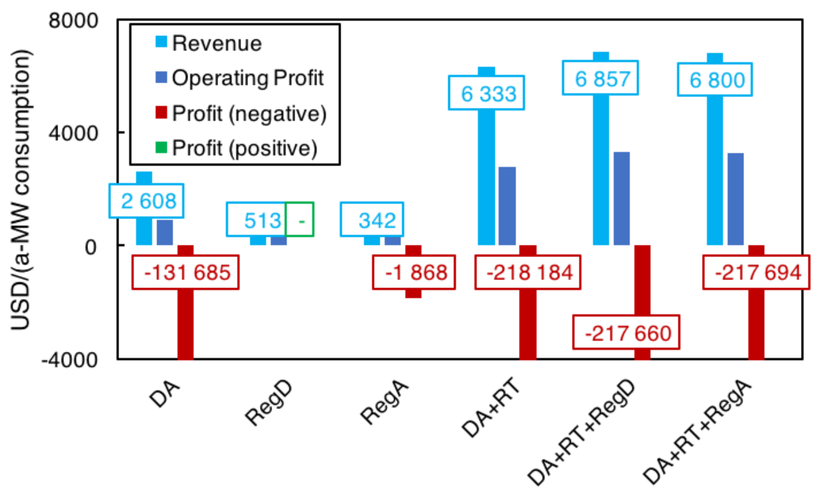

Figure 5.13: Market size of ESS in PJM electricity markets in the scenario of "max. Revenue"

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 5.2; 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 5.14.

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

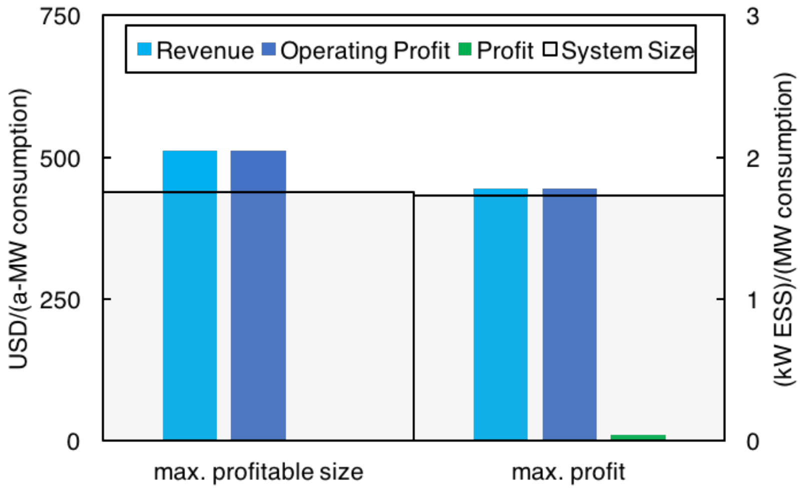

Figure 5.14: Market size of ESS in PJM electricity markets in the scenario of “max. System size with pos. Profit” and “max. Profit”

improve the profitability and tangible market size as significantly as in Germany. As we can see from an example shown by Figure 5.15, 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 5.2, 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 5.2, 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

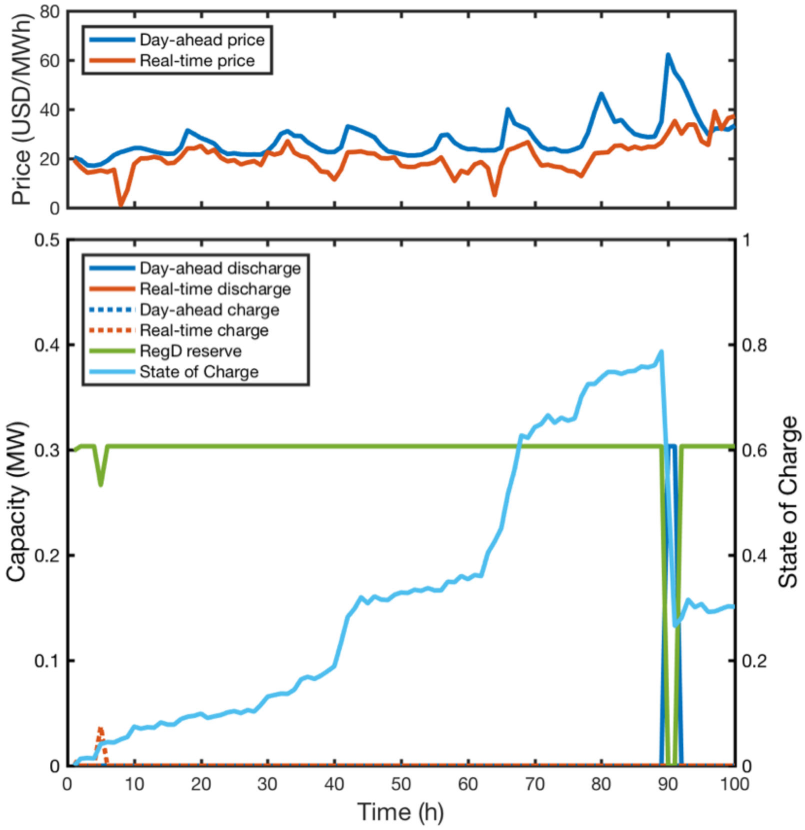

Figure 5.15: A example of operational plan with a 0.3MW battery energy storage system

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 5.10.

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 5.17. This reflects the philosophy of market design to fully exploit the ability of real-time energy market to re-sponse to the system imbalances which are otherwise tackled by frequency control markets [139] [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 5.5.

Table 5.5: 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

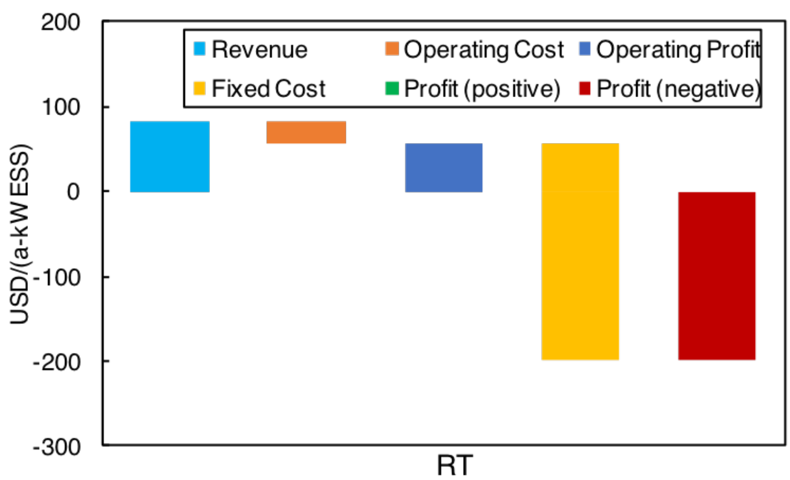

Figure 5.16: Profitability of ESS in NSW electricity markets in the scenario of "max. marginal Revenue"

Such a volatile market is favorable for arbitrage. As we can see from Figure 5.16 and 5.17.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.

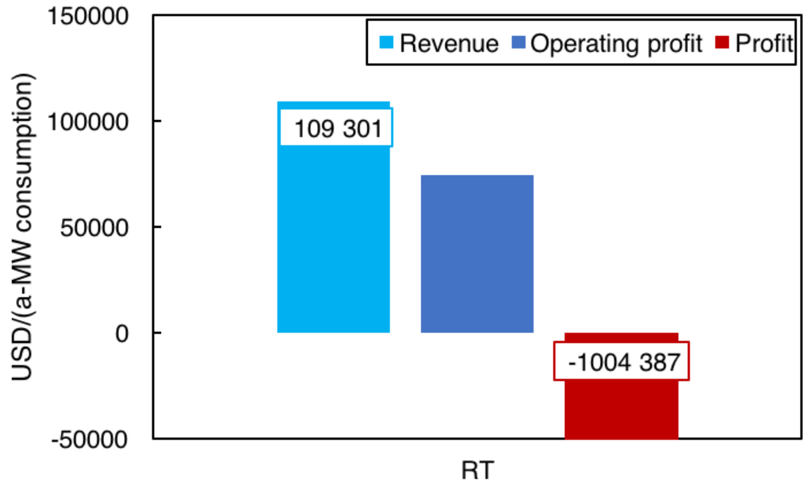

Figure 5.17: Market size of ESS in NSW electricity markets in the scenario of “max. Revenue”

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 5.18 - 5.20 illustrate how the profitability and market size will evolve with cost reduced by up to 95% in three geographies. The break-even

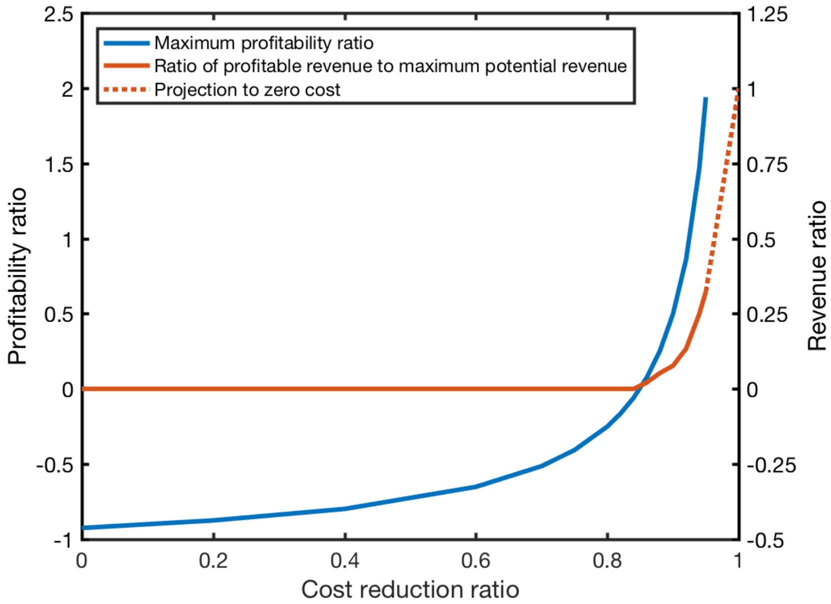

Figure 5.18: Development of market size and profitability of arbitrage in coupled day-ahead and intra-day markets with reduced costs in Germany

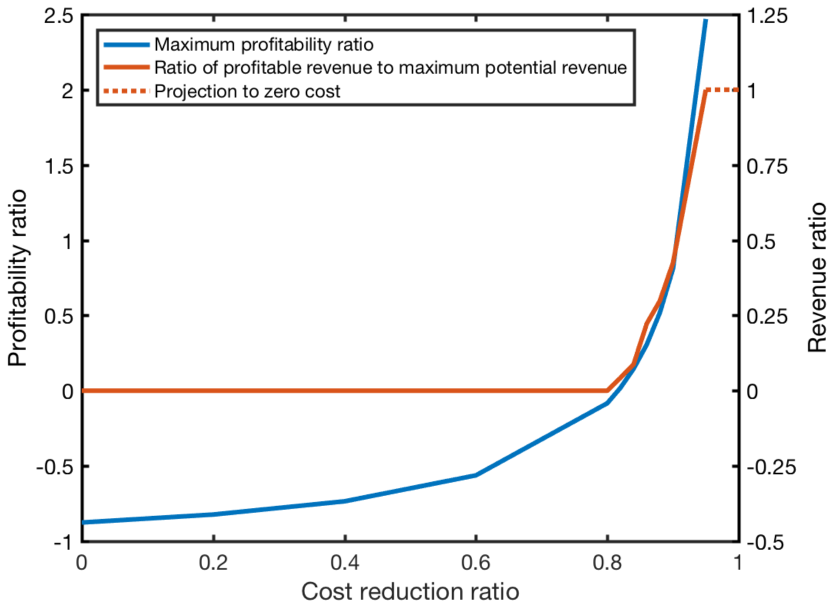

Figure 5.19: Development of market size and profitability of arbitrage in coupled day-ahead and real-time markets with reduced costs in PJM

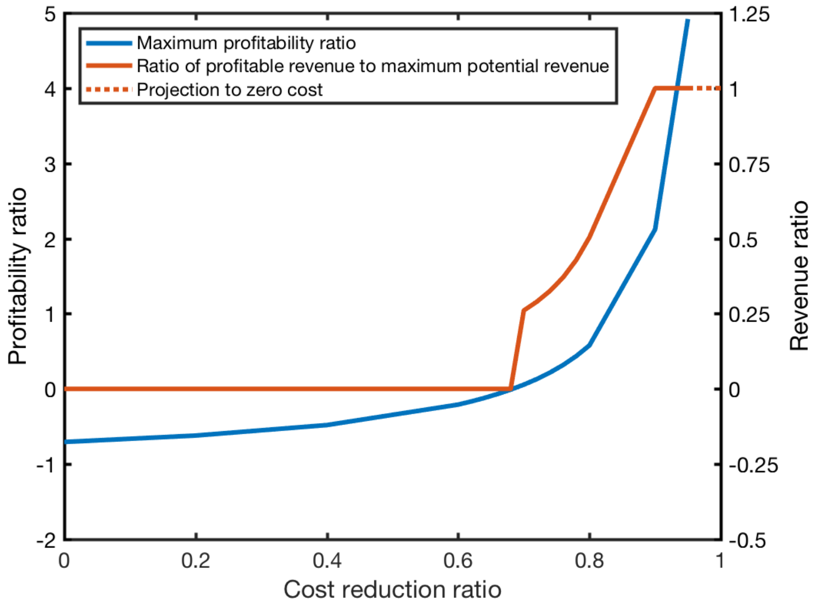

Figure 5.20: Development of market size and profitability of arbitrage in real-time markets with reduced costs in NSW

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 [168] 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 5.3.3.

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 5.21, 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.

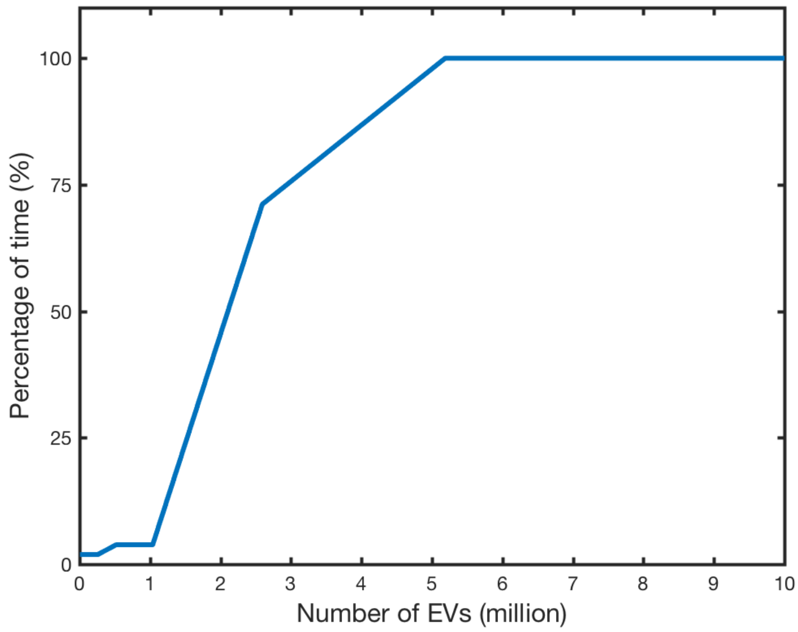

Figure 5.21: Percentage of time when EV charging demand cannot be fulfilled in Germany

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 [177]) i.e. 0.9 million EVs in the future

According to the Federal Motor Transport Authority of Germany (Kraftfahrt-Bundesamtes, KBA) [178], 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 5.22.

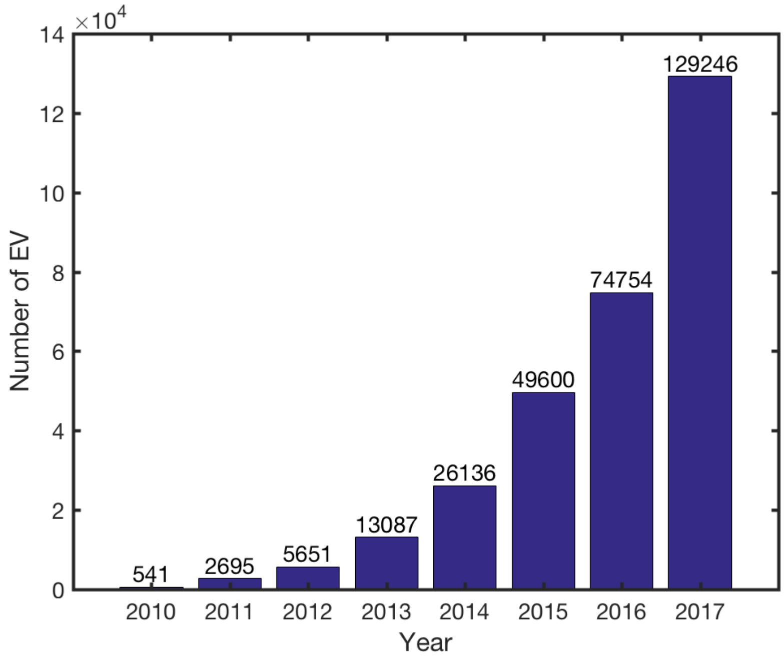

Figure 5.22: Cumulative registration of plug-in electric vehicles in Germany since 2010 [178]

The numbers of EV that were taken for the scenario analysis are then determined and list in Table 5.6.

Based on these scenarios, we performed the case studies and the results are shown by Figure 5.23. 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 5.6: 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

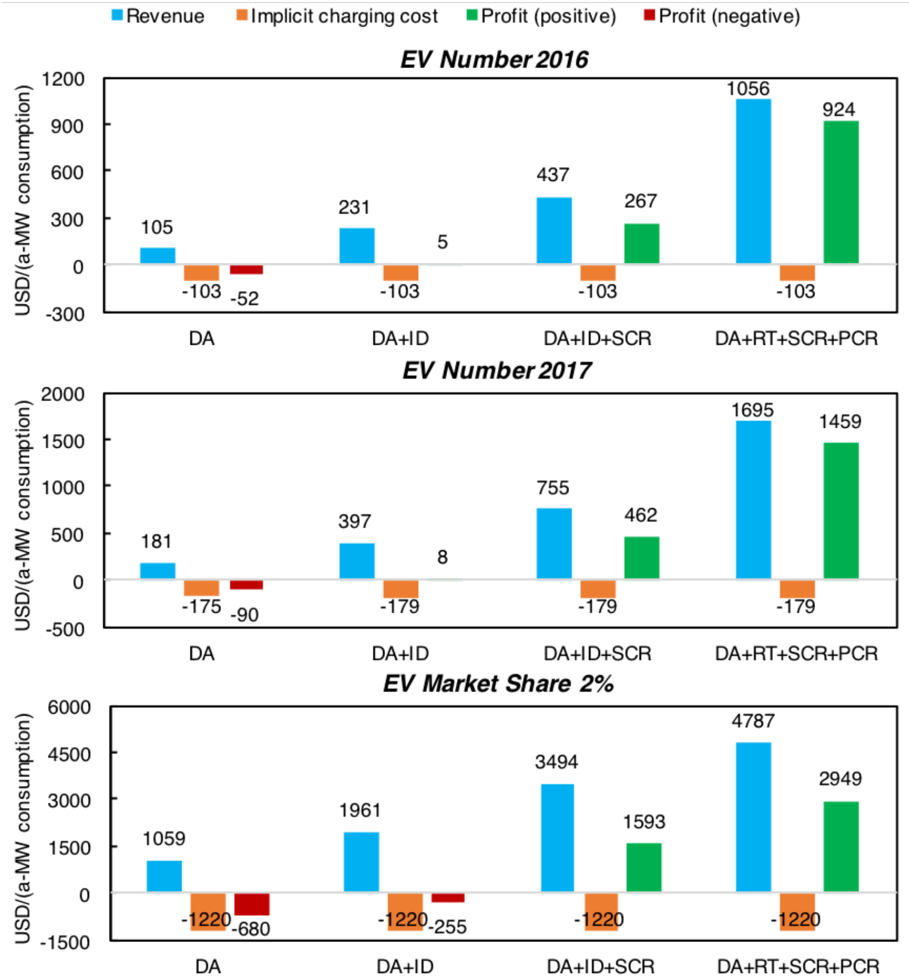

Figure 5.23: Market size and profitability of EV2G in Germany electricity markets

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 [113] [86] [179] [180], 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 5.7 shows the number of EV in each scenario.

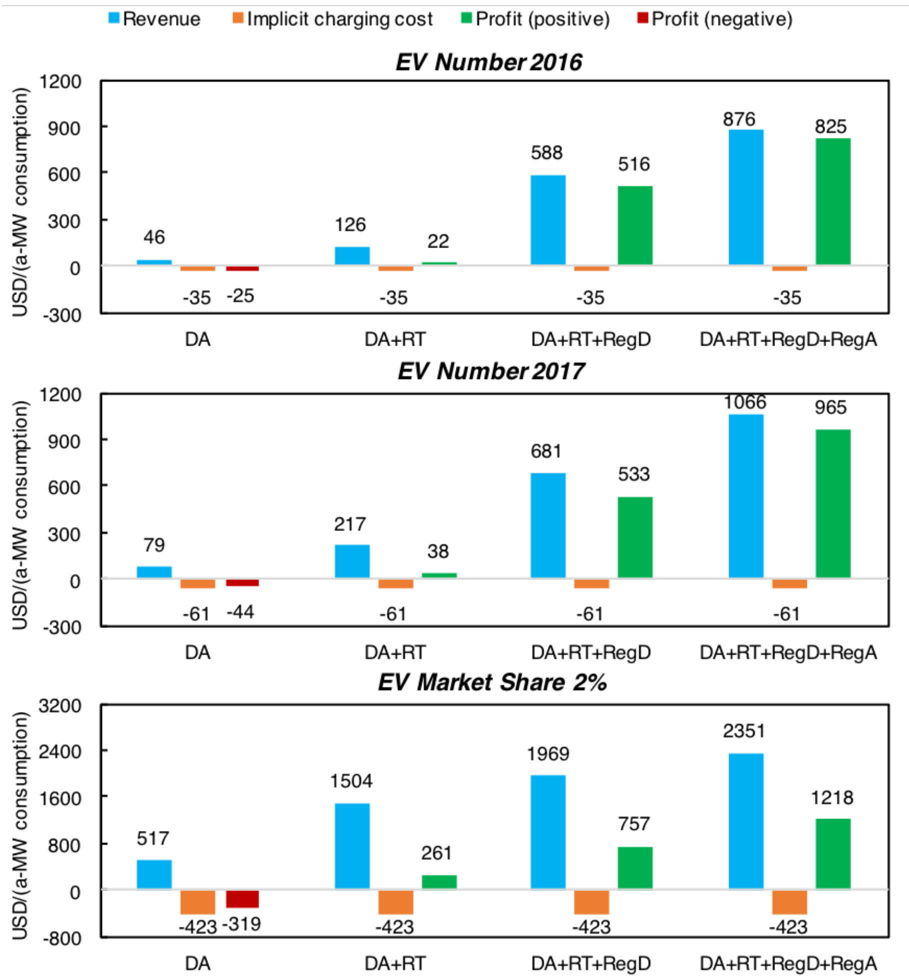

Figure 5.24: Market size and profitability of EV2G in PJM Electricity markets

Table 5.7: 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 5.24 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 5.13. 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 5.8. With these number of EV, no supply shortage was observed.

Table 5.8: 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 5.25 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 5.17, leaving a vast space for other technologies.

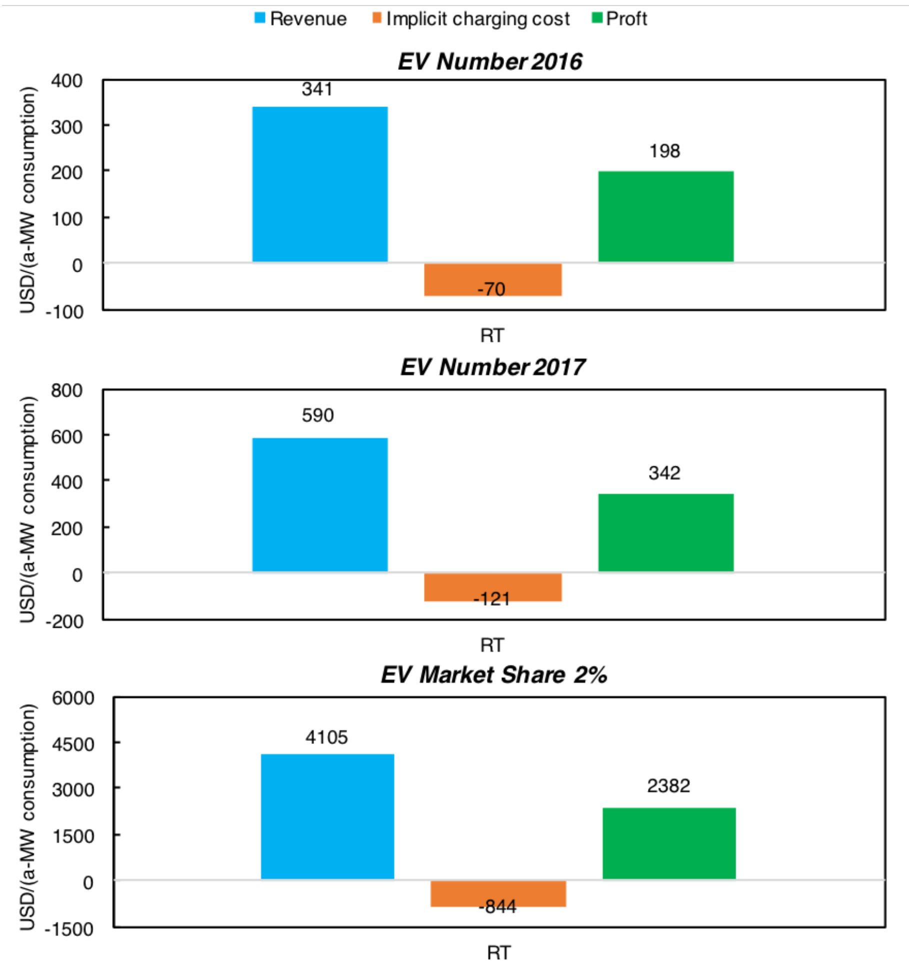

Figure 5.25: Market size and profitability of EV2G in NSW Electricity markets

Summary

The key indicators for the market size and profitability, in both normalized and absolute values are summarized in Table 5.9-5.11. 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 5.9: 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 5.10: Summary of market size and profitability of flexibility management in PJM

Item[a]	**Arbitrage** DA+RT	**Balancing** RegD	RegA	**Multitasking** 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 5.11: 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

5.3.3 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. Dayhead 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 5.26.

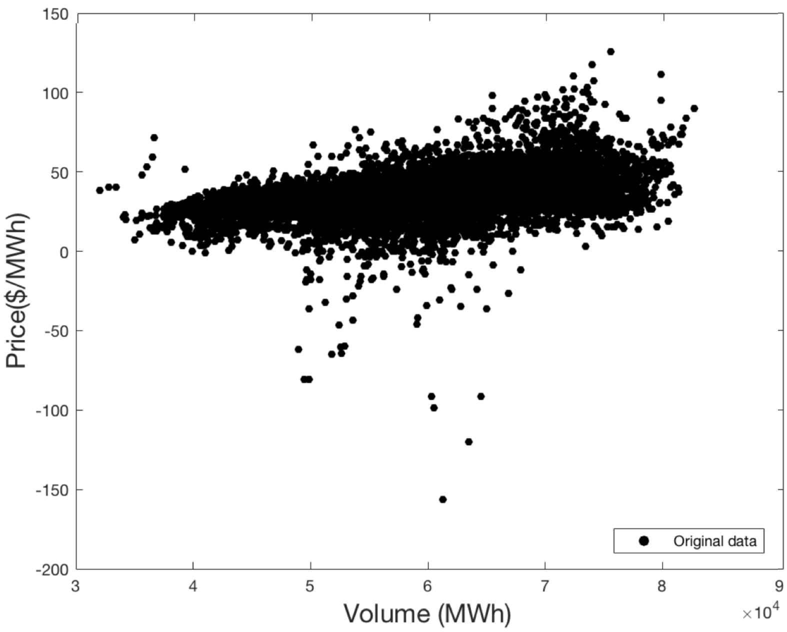

Figure 5.26: Germany day-ahead price-volume data in 2016

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 [157] [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 5.27 shows the transformed pattern of data where a clearer merit-effect is identifiable. Figure 5.28 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.

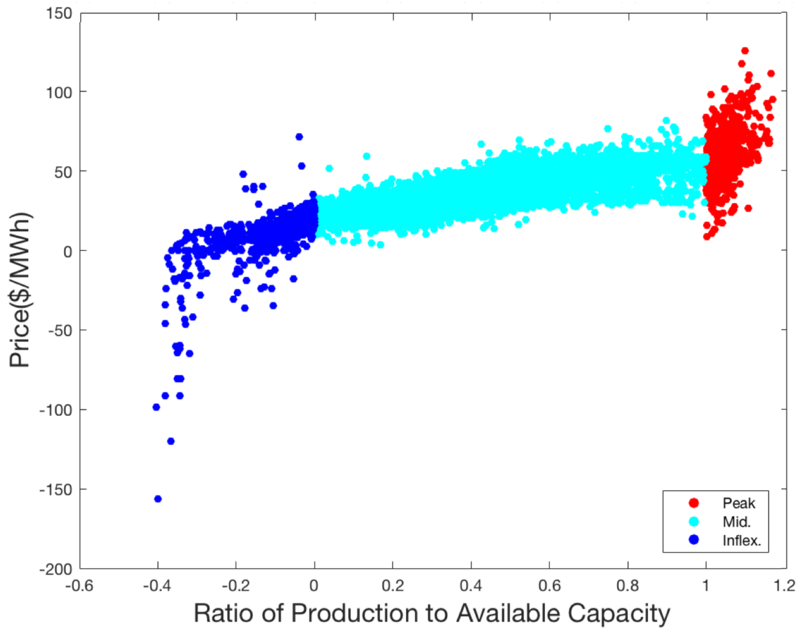

Figure 5.27: Transformed pattern of Germany day-ahead price-volume data in 2016

Thereafter, we fitted the transformed data pattern with the piece-wise function defined by (4.17). The estimated parameters are listed in Table 5.12. It shall be noticed there are price limits applied in EPEX day-ahead market [181] 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 5.29 and distribution of errors between the fitted price and actual price is shown by Figure 5.30.

Table 5.12: 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 5.29-5.30 that while the fitted merit-order price shows a good fitness to the actual price in

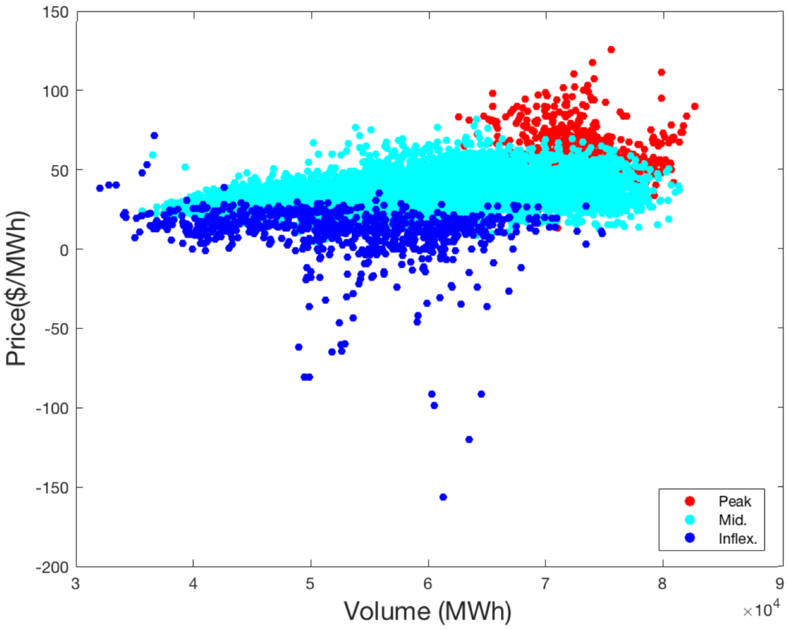

Figure 5.28: Classification of Germany day-ahead price-volume data in 2016

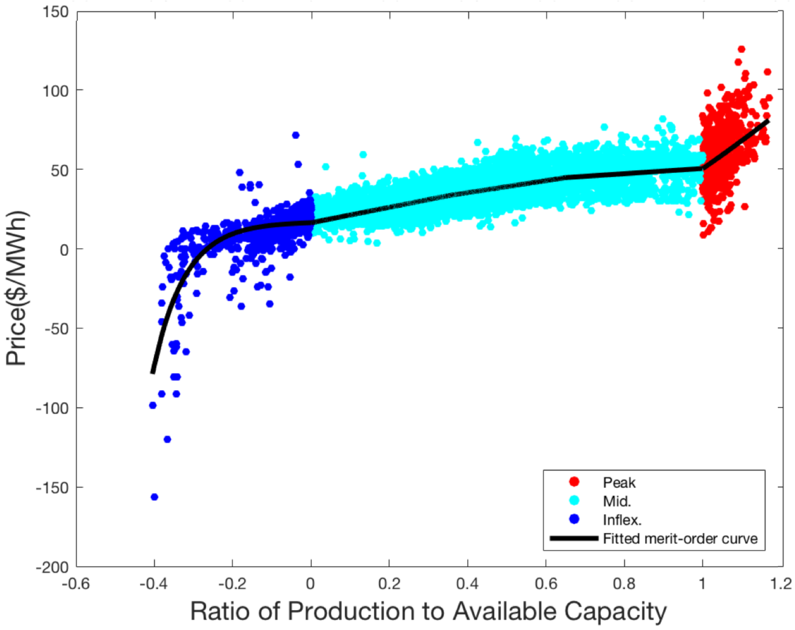

Figure 5.29: Fitted merit-order curve with Germany day-ahead price-volume data in 2016

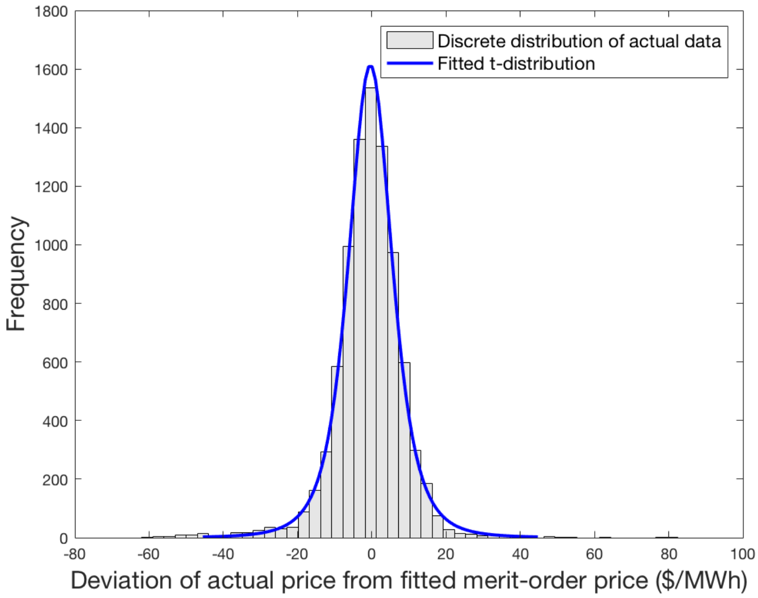

Figure 5.30: Distribution of errors between fitted merit-order price and actual price

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 5.31.

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 5.32. 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 5.13: Parameters of the stochastic price movement of SARMA models in Germany

SARMA parameters	
$\omega_1 = 1.811$	$\theta_1 = -1.063$
$\omega_2 = -0.813$	$\theta_{24} = 0.692$
$\omega_{24} = 0.090$	$\theta_{168} = -0.600$
$\omega_{168} = 0.692$	

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

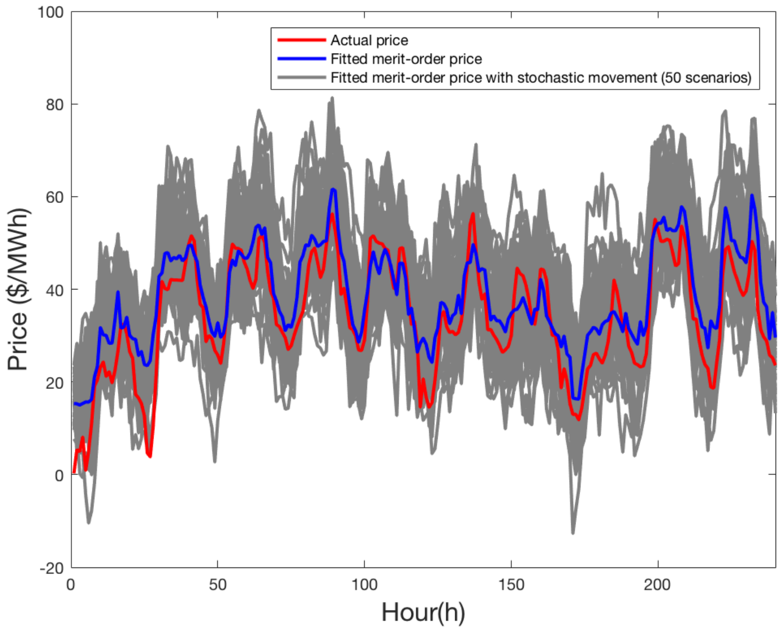

Figure 5.31: Generated price scenarios

the error signal characterized by5.30 is listed in Table 5.13. 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 5.31. 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 5.32. 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 [182]. 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 [183].

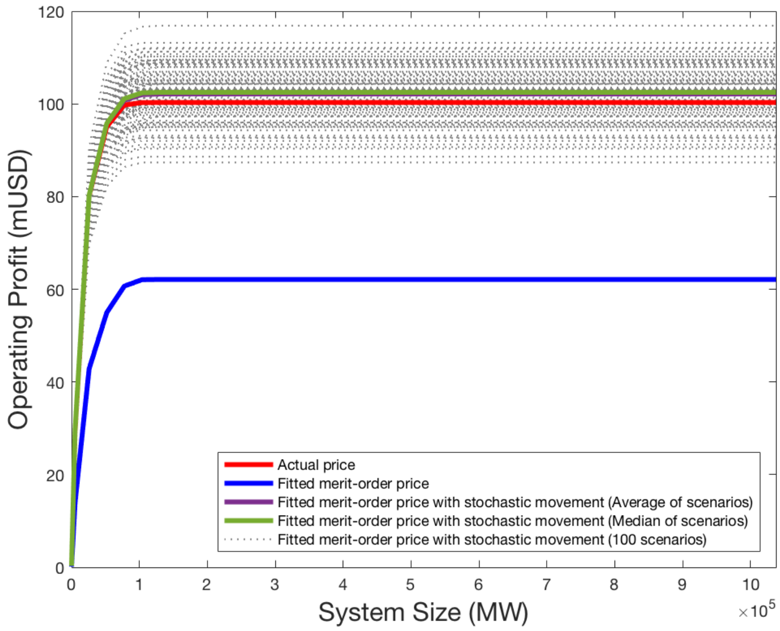

Figure 5.32: The revenue with different price scenarios for model validation in Germany

The parameters for the merit-order model in PJM are listed in Table 5.14. The SARMA parameters are presented in Table 5.15.

Table 5.14: 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 5.15: Parameters of the stochastic price movement of SARMA models in PJM

SARMA parameters	
$\omega_1 = 0.690$	$\theta_1 = 0.107$
$\omega_2 = 0.125$	$\theta_{24} = -0.003$
$\omega_{24} = 0.298$	$\theta_{168} = -0.399$
$\omega_{168} = 0.560$	

Renewable penetration in Germany: at the inflection point

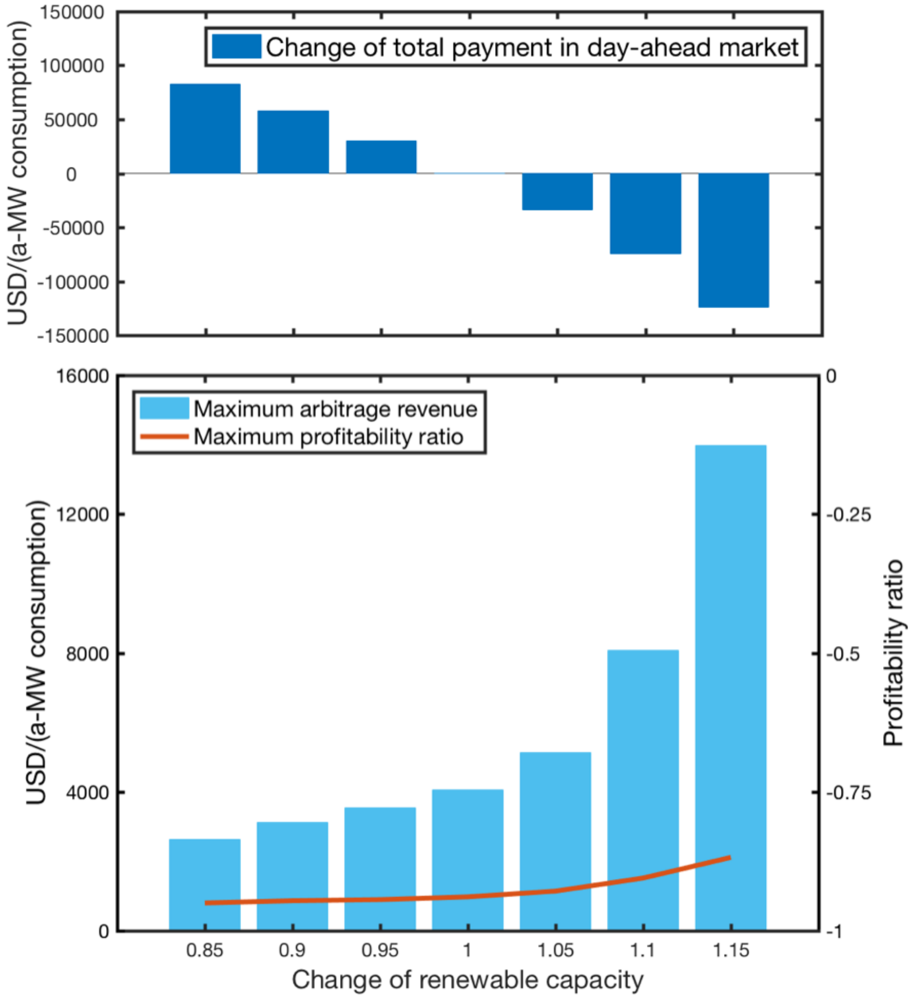

Figure 5.33: Impacts of renewable generations on revenue and profitability of arbitrage using flexibility as well as on total amount of transations in day-ahead market in Germany

The results are illustrated in Figure 5.33. 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 5.2.

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 5.3.4 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 5.34. 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) [182]. However,

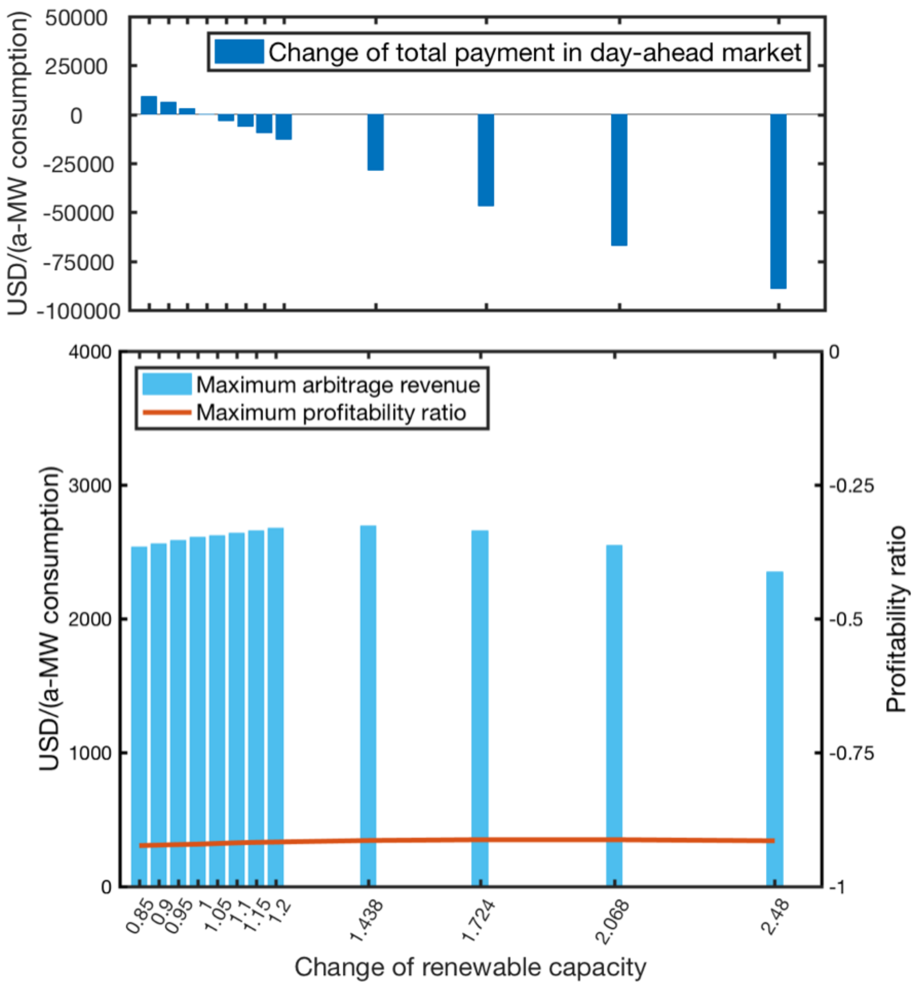

Figure 5.34: Impacts of renewable generations on revenue and profitability of arbitrage using flexibility as well as on total amount of transations in day-ahead market in PJM

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

5.3.4 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 5.16 to 5.18.

Table 5.16: 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 5.17: 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 5.18: 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

Outlook:

Price evolution of frequency control markets

Appendix A

Accounting rules and electricity market data preparation

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1	Day-ahead energy market
2	Real-time energy market

1	Day-ahead energy market
2	Intra-day energy market
3	Balancing energy

1	Primary control reserve
2	Secondary control reserve up
3	Secondary control reserve down

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