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Challenges Arising from the European Sequential Electricity Market Design: Market Power and Intraday Market Issues

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Introduction

Today's restructured electricity markets illustrate the importance and power of effective market design. Over the last 25 years, electricity markets have evolved to address complex economic and engineering challenges. Despite some impediments along the way, the markets have largely succeeded in the goal of providing reliable electricity at least cost to consumers. This is no simple task. Every second, supply and demand must balance. Thousands of resource and network constraints must be satisfied. And the market must send the right price signals to motivate efficient generation and investment in resources over time.

The complexity of the economic problem that the market must solve makes the market design complex. Good electricity market design has always been important. Design mistakes can cost consumers tens of billions of dollars, as illustrated by the California electricity crisis of 2000 and 2001 (Borenstein (2002)). Fortunately, because of good governance and technological progress, market designs have improved over time. Flaws have been identified and largely addressed.

Electricity market design still needs steady improvement. New challenges are emerging with the ongoing transformation of the electricity industry. These modern challenges are the huge integration of renewables, demand response, distributed generation, smart homes, and battery storage. The electricity market design must be able to handle this transformation.

There are many different electricity market designs around the world mainly due to the diverse economic and political tastes as well as technical differences. But all market designs must address variety of important issues such as:

- Transmission network and generation resources restrictions must be considered to impede the failure of equipments.
- Demand and supply uncertainty originating from generators or network failure or intermittent generation from solar and wind resources.
- Momentarily supply and demand balance.

Cramton (2017) categorizes market designs into two main groups: 1- integrated market and 2- exchange-based market.

Based on his description, in the integrated markets, by a central optimization, the system operator finds the optimal scheduling and dispatch of all generation units. Hence, the system operator has access to the detailed and private cost and technology information of each unit. Even though the market is centralized, market participants have enough freedom for their decentralized decisions. This centralization on market clearing and dispatch lets the system operator to simultaneously reach reliability and economic efficiency objectives. This model is the dominant market design utilized in most of North America. North America spot markets composed of two day-ahead and real-time markets. Both of them are utilizing very complex optimization techniques and hardware. In order to give a clue on the size of the problems, the Texas market -which is run by its independent system operator (ERCOT)- is given as an example. By using thousands of computer servers, ERCOT is like a smart market. In order to reach to the highest possible welfare, optimization is done subject to the very sophisticated bid/offer curves and constraints. In the day-ahead market, participants submit bids and offers not only for energy but also for reserves for each hour of the next day. The result of the day-ahead clearing is a schedule of generation units with hourly locational marginal prices. The day-ahead market allows participants to efficiently utilize their physical assets by ahead planning and hedge against volatile real-time prices. The real-time market is a 5-minute bid-based security-constrained economic dispatch of generation resources along with 5-minute locational prices.

On the other hand, in exchange-based markets, there is not a centralized optimization like the first case but generation companies trade at spot markets by cleared prices. Most European markets tend to follow this model. Despite all efforts put into integration of European markets by Euphemia and XBID projects to integrate day-ahead and intraday markets respectively, still they can be considered as more fragmented markets than in the US. This fragmentation particularly originates from national preferences with limited cooperation possibilities across countries. The most crucial difference between US and Europe markets is on how the transmission network is modeled. Locational price signals are much weaker in Europe, because usually prices are cleared for larger zones that are composed of several nodes. By zonal simplification, either within or across countries, transmission congestion is not efficiently priced. Cramton (2017) suggests that European-wide commitment and dispatch of resources along with a more efficient congestion pricing could bring considerable benefits, particularly in the case that rapid integration of renewables put significant pressure on the transmission network.

European spot markets are composed of three sequential markets: day-ahead, intraday and balancing markets. In the first two markets the simplified zonal structure based on either Available Transmission Capacity (ATC) or Flow-based approach is utilized. In real-time, a voluntary balancing market which tends to be thinner than the US real-time markets is run. Since this balancing market is more simplified than the security-constrained economic dispatch of the US, less reliable real-time prices may appear. Hence, the need for intraday trading increases since it provides an opportunity to resolve imbalances ahead of real-time.

It seems that the advocates of financial exchanges tried to persuade electricity regulators to model intraday electricity market as a continuous trading market, similar to stock market. Even though Henriot (2012a) and Hagemann (2013a) point out that continuous trading is superior to discrete auctions from ease of trade point of view especially for intermittent generators to balance their forecast errors before delivery time, it has been shown in many other papers that this method just encourage speed rather than optimal trading. Moreover, continuous trading is not suitable for electricity markets, because it is based on bilateral trades while Wu and Varaiya (1999) prove that to relieve congestion of just one congested line at least a 3-lateral trade is required. Therefore, if we are eager to consider both aspects speed and optimal feasibility of trades, more frequent intraday auctions seem to be more reasonable.

With respect to these explanations, I reckon that the European sequential market design needs to be further investigated to see whether market objectives which are short-term and long-term efficiency have been attained yet. The aim of this thesis is to find the major deficiencies of the current design and to present the remedial or alternative market designs. Hence, chapter 2 focuses on the potential of market power exercise in the current design and the other chapters spotlight the different intraday market designs and the issues coming from each design.

In chapter 2, "market power under nodal and zonal congestion management techniques", it has been shown that one of the challenges that European sequential market design can arise is providing some opportunities to exercise market power. The main reason of such issue is the different congestion management techniques utilized in the day-ahead market than in the real-time (balancing) market. In European zonal markets, at the day-ahead stage, the physical transmission lines are partially neglected; meaning that the intra-zonal lines are neglected and just cross-border inter-zonal capacities are modeled by Available transmission Capacity (ATC) or flow-based models. Then at the real-time stage, all physical transmission constraints are captured based on Kirchhoff's law. In this paper, the market power potential of nodal model (wherein the same congestion management technique is utilized at both day-ahead and real-time with full transmission constraints) is compared with ATC and flow-based zonal models. By a simple 3 nodes (2 zones) illustrative example, we show that despite the common objection to nodal pricing that has the more potential of market power in zonal models the need for redispatch at real-time (to make the day-ahead result feasible with respect to physical transmission constraints) creats a place for gaming. Our results show that in zonal ATC model, market power could be very dependent on the ATC levels and therefore this model has the highest potential of market power among others. Above all, infinite ATC which is equivalent to uniform pricing model is the worst case. Our results do not show very different surpluses for strategic player in various flow-based models than in the nodal model, although the social surplus of nodal model with a great difference is higher than the other models.

With the large-scale penetration of intermittent resources in the Europe, it becomes more challenging for market participants to be in balance between day-ahead and real-time markets. Therefore, intraday market has been designed and now the integration of all European intraday markets is on the agenda. As mentioned before, the intraday market follows the same congestion management technique as day-ahead. Hence, the imbalances due to the network simplification still exist. In the current continuous trading market, whenever a matching happens the shared order book (SOB) calculates the required quantity to be transferred between the source and destination zone. Then capacity management module (CMM) is responsible to find an optimal routing plan by minimum cost flow routing problem to select routes with minimum cost satisfying the flow constraints over cross-border interfaces. But these interfaces are not reflecting the physical transmission network. Consequently, it is still very probable that the trades occur in the intraday market lead to infeasible flows and therefore imbalances in the real-time market. In chapter 3, I will show that in addition to its original functionality, intraday market can also be designed such that gradually and by an iterative procedure feasible flows are achievable at the end of the intraday market. By customizing the coordinated multilateral trading (CMT) approach to the current European structure, our model is able to reach to the optimal nodal solution, provided that all circumstances such as bid and offers remain unchanged and no uncertainty is modeled. By these assumptions and running day-ahead market with different ATCs, we reach to the conclusion that irrespective of what ATCs are adopted in the day-ahead market, at the end of the intraday market optimal nodal solution is achievable. This means that no imbalances occur in the real-time market due to the network violation.

The recent decision of the European commission to integrate intraday markets by continuous trading through XBID project launches new challenges regarding to the pricing of cross-zonal capacity. Consequently, recently agency for the cooperation of energy regulators (ACER) has decided to complement the already established continuous trading intraday with three pan-European auctions (ACER, (2019)). Once the necessity of having intraday auctions proved, the next question is the optimal timing of these auctions. Decision on timing of auctions is heavily dependent on two factors: the share of uncertain production and flexibility of the system to respond to that uncertainty. By getting closer to the delivery time, the forecast errors and therefore uncertainty is declining while the flexibility of the power system decreases and the related cost increases. In chapter 4, the optimal timing of one intraday auction in the presence of wind uncertainty and flexibility costs is examined. For a specific delivery hour, the day-ahead economic dispatch problem with expected wind power at delivery hour is optimized. Then for 3 intraday places, optimal re-adjustments are done to correct expected wind deviations from day-ahead market. Likewise, the final optimal reschedule is done in real-time to cope with the real wind deviations from intraday. By testing several scenario trees with uncertainty reduction characteristic from day-ahead to real-time, a tight trade-off between these two factors has been observed. Our findings reveal that even though standard deviation reduction is an important measure for uncertainty its reduction is not enough to say that always the latest intraday is the best by assuming the other variables as fixed. Therefore, the standard deviation reduction is mainly reflected in re-adjustment quantities. This means that the more STD is reducing from day-ahead to real-time, the more re-adjustments are required and finally, in the sequential market setting that the expected wind power is utilized for clearing stochastic generators, the multiplicative effect of flexibility cost and re-adjustment quantities determine the best intraday place not the trade-off between flexibility cost and STD reduction.

In most papers on intraday market design, the continuous trading structure of this market has not paid too much attention. Limit order book is the tool for continuous trading operation. In chapter 5, I focus on limit order book modeling and simulation wherein market participants (intermittent and conventional generators, elastic demands and financial traders) randomly submit market orders or limit orders with random quantities chosen from their residual capacity or cleared capacity (depending on ask or bid order submission) and marginal cost as the submitted price. The model is able to manage the order arrivals, their addition to the list (as limit order) or matching them with the best available opposite order (market order), store the matched trades, update the quantities of matched orders and lastly accept part (or whole) of matched order to maintain the feasibility of transmission network with respect to the nodal constraints of the network.

Before going through the other chapters of the thesis, further introduction to European intraday market, the relevant terms and terminologies and specifically integration of intraday markets with XBID project will be reviewed in the following subsections of introduction chapter.

1.1 An overview over European intraday markets and the cross-border integrated intraday market (XBID)

The integration of electricity markets when transaction is allowed among entities from different market areas is refered to as market coupling. Meeus et al. (2009) and Hobbs et al. (2005) show that market coupling can be considered as an important instrument for increasing economic efficiency. In a coupled market, demand and supply orders in one market are no longer confined to the local market. On the contrary, energy transactions can involve sellers and buyers from different areas, only restricted by the electricity network constraints.

The main benefit of the market coupling approach is to improve the market liquidity along with the less volatile electricity prices. It is also advantageous for market participants. They no longer need to acquire transmission capacity rights to conduct cross-border exchanges, since these cross-border exchanges are the result of the market coupling mechanism now. They only have to submit a single order in their market (via their corresponding PX) which will be matched with other competitive orders in the same market or other markets (provided that enough electricity network capacity is available).

In this regard, after the successful experience of implementing *Price Coupling of Regions (PCR)* that aims to integrate all European day-ahead markets, the *Cross-border Integrated Intraday Market (XBID)* project is high on the agenda. The XBID project is a joint work by four power exchanges (PXs) - EPEX SPOT, GME, Nord Pool and OMIE - together with the transmission system operators (TSOs) from eleven countries, to create an integrated intraday cross-border market. The coupled intraday market enables continuous cross-border trading across all of Europe.

The benefits of intraday market coupling mentioned in the related official documents (NordPool (2016a)) are the following:

1. A cross-border trading opportunity within the day across Europe on a consistent platform
2. More efficient utilization of generation resources across Europe, especially variable renewable energy sources
3. A complement to the existing day-ahead market
4. The capability of delivering a wide range of products - 15 minutes, 30 minutes, hourly and block products and a wide range of order types which provide easier trading possibilities

XBID enables the continuous matching of orders from market participants either in the same market area or from any other market area provided that cross-zonal capacity is available. It comprises three main modules and each of them performs part of the algorithm tasks: the Shared Ordered Book (SOB), the Capacity Management Module (CMM) and the Shipping Module (SM). The combined entity allows multiple power exchanges in different geographical places to trade cross-border energy products continuously on a centralized platform. In the following sections the relevant XBID terminology and the different XBID modules will be presented.

1.1.1 Terminology

- **Delivery area**

  Is the smallest element in the transmission network which is managed by one TSO. Market participants that are physically connected to those TSOs can submit their orders with reference to the delivery area they are connected by. The information related to the source and destination delivery area of the matched trades is also recorded. Each delivery area is assigned to a market area.

- **Market area**

  Illustrates an uncongested price area, meaning that the transmission capacity between market areas is subject to the congestion. Each market area can contain more than one delivery area. There is not any transmission capacity limitation between delivery areas within the same market area.

- **Interconnector**

  Is a connection between two delivery areas. An interconnector $A \rightarrow B$ is a directional connection between source delivery area A and destination delivery area B. Only one interconnector per direction and pair of delivery areas is considered. If there is an interconnector in one direction, the interconnector in the opposite direction must also exist which is called the reverse interconnector.

- **Border**

  Is a connection between two market areas.

- **Path**

  A path $A \to B \to ... \to Z$ is a sequence of distinct delivery areas in the grid where subsequent areas of the path are connected by interconnectors. The first delivery area of a path is called the source of the path and the last delivery area of a path is called its destination. A path cannot contain the same delivery area more than once, meaning that no loop is allowed.

- **Available transmission capacity (ATC)**

  ATC is an interconnector attribute indicating the maximum available amount of power that can be transported in the direction of the interconnector. The ATC quantity varies per period and changes after each capacity allocation.

- **Flow**

  A flow is an interconnector attribute indicating the flow of power in the direction of the interconnector that is used in the routing calculation. The value cannot be negative and must be smaller than or equal to the ATC.

- **Capacity information**

  Everyday the involved TSOs announce the transmission capacity of their own interconnectors or borders for both direction. They provide two values: Net transfer capacity (NTC) which conveys the physical transfer capacity of the interconnectors or borders and already allocated capacity (AAC).

- **Cost coefficient**

  Is an interconnector attribute indicating the mathematical cost of a flow. It must be a positive value. This coefficient is independent of the period and determines over which path power should be routed preferably. It has no financial bearing and is only a mathematical construct to make a distinction between interconnectors in terms of routing priority. Interconnectors with a lower cost coefficient will be prioritized over interconnectors with a higher cost coefficient. The cost coefficient is direction-independent, i.e. it is the same for an interconnector and its reverse. The default value of a cost coefficient is 1.

- **Transport**

  Is the transfer of power through the grid, determined by a path and a quantity. A cross-border trade may require the transportation of power on several paths, i.e. a set of transports.

- **Network flow**

  A set of transports starting at the same source and ending at the same destination can be gathered into a network flow. Network flows are obtained by merging multiple transports where parallel and opposing flows are combined per interconnector in common, the resulting network flow on this interconnector is the sum of the flows of the individual transports.

- **Internal netting**

  When the paths of two transports share the same pair of adjacent areas with flows in opposite directions or in other words, if a certain interconnector is part of the first transport and its reverse is part of the second transport, then internal netting is applied on that interconnector and its reverse.

  If the path of one transport includes an interconnector that is the reverse of an interconnector in a second transport, the magnitude of the resulting network flow is the absolute value of the difference of the two individual transport flows in the direction of the interconnector with the flow value that was larger initially.

1.1.2 The Capacity Management module (CMM)

The Capacity Management Module is a module in which cross border capacity between connected market areas is managed. The main components of the CMM module are delivery area, market area, interconnector, border and capacity information. The CMM supports separate (independent) configuration and administration of each functional entity shown in Figure 1.1. Figure 1.2 illustrates a clearer understanding of these definitions.

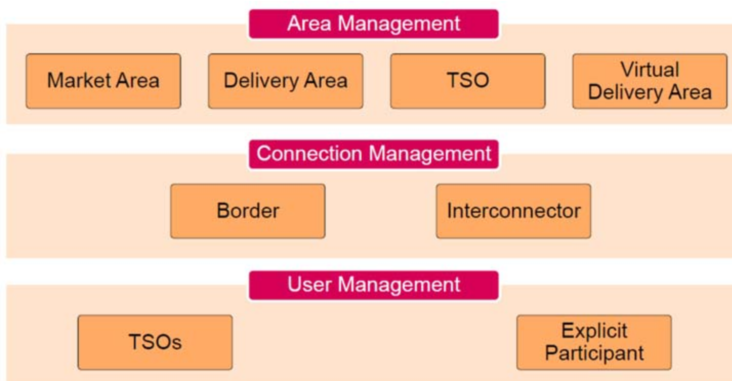

Figure 1.1. CMM entities (Verseille and Alaimo (2018))

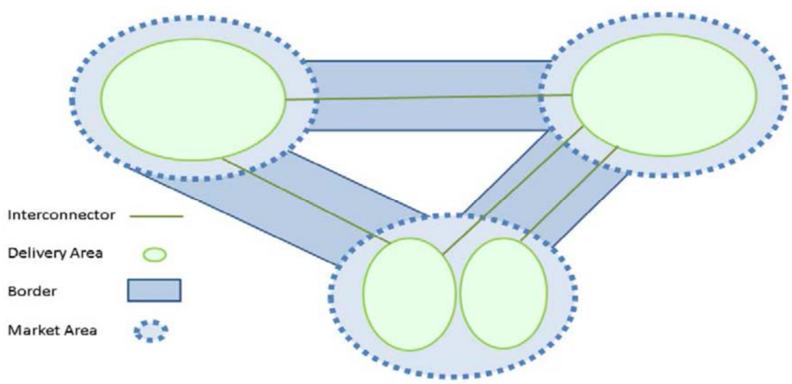

Figure 1.2. CMM configuration setting (Verseille and Alaimo (2018))

In order to allow feasible trades between different market areas, enough transmission capacity is needed. The involved TSOs use the CMM module to allocate available transmission capacity (ATC).

With respect to these daily inputs, the ATC for each border is calculated as follows: $ATC_{A\to B} = NTC_{A\to B} - AAC_{A\to B} + AAC_{B\to A} - \text{intraday allocations}_{A\to B} + \text{intraday allocations}_{B\to A}$
$ATC_{B\to A} = NTC_{B\to A} - AAC_{B\to A} + AAC_{A\to B} - \text{intraday allocations}_{B\to A} + \text{intraday allocations}_{A\to B}$

Figure 1.3 shows the European CMM topology.

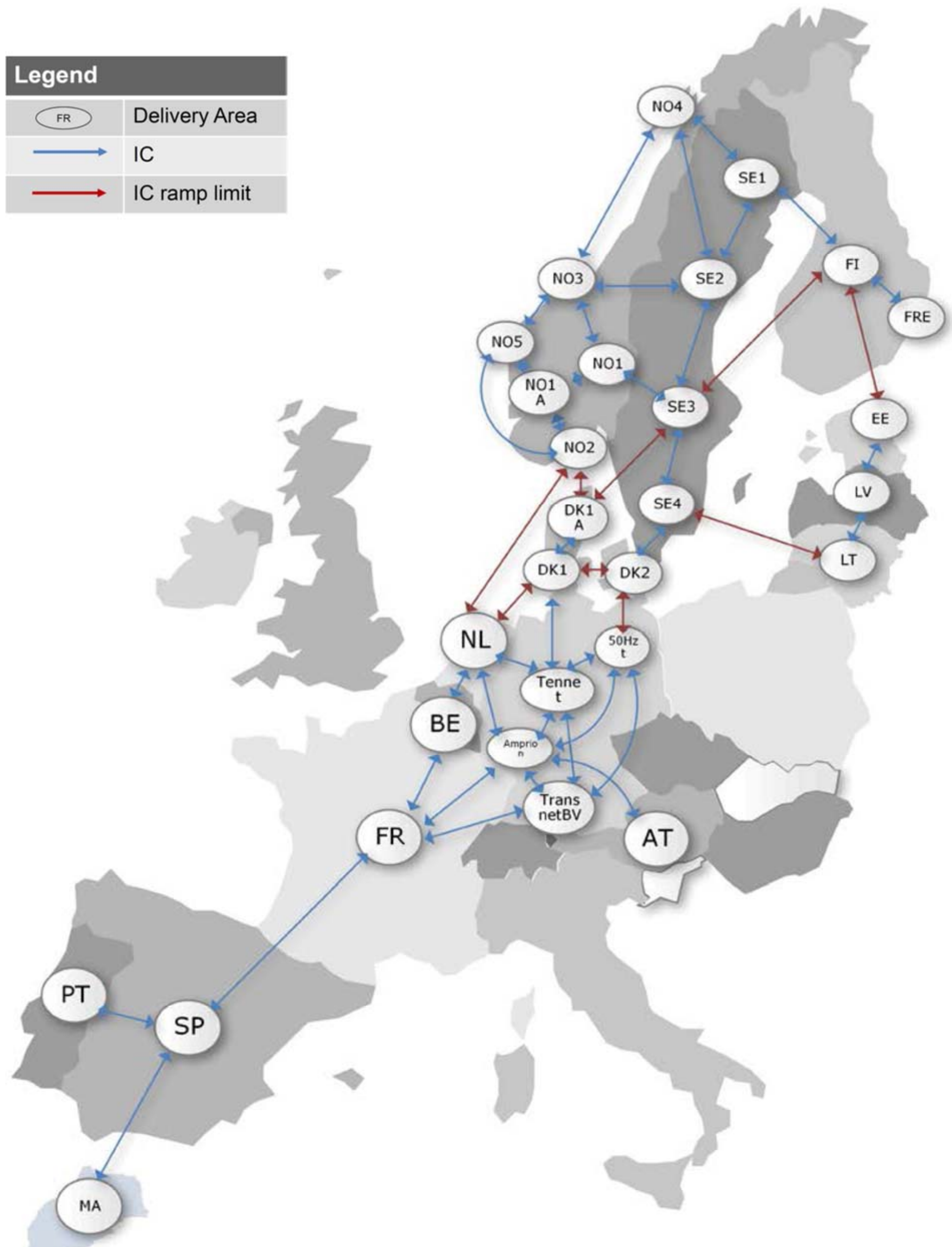

Figure 1.3. European CMM topology (Verseille and Alaimo (2018))

1.1.3 The Shared Order Book (SOB) module

The Shared Order Book module is a consolidated order book that connects the local order books of the involved delivery areas. This module accommodates the basic functionality for continuous trading, like order entry, order management and order matching. It also initiates the capacity allocation. The two main components of the limit order book are *products* and *orders*.

1.1.3.1 Products

Products are defined based on their delivery duration. The XBID system supports the following types of products:

- 15-minutes
- 30-minutes
- 60-minutes
- User-defined hourly block products

Products have a trading unit (MW) and a trading currency (it could be any type of currency, although Euro will probably be used most of the time). Figure 1.4 illustrates a snapshot of the shared order book which is visible in the delivery area of SE3 (third delivery area of Sweden). For instance, *PH* is a 60-minutue product while *4H* shows a 4-hour block product, etc.

Figure 1.4. Shared order book (NordPool (2016b))

1.1.3.2 Orders types

- **Limit order**

  Reflects the maximum willingness to pay (bid) or the minimum willingness to accept (ask) for each unit (megawatt hour) of the specified quantity of a given product. As Figure 1.4 shows, bids and asks are sorted respectively in descending and ascending orders. These sortings let the current "best offers" to be located at the top of the order book. The highest bid price 54 in Figure 1.4 is less than the lowest ask pric 59, which implies that the highest willingness to pay among the buyers is not sufficiently high to encourage a seller to trade. The magnitude of the difference between the prices at the top of the order book is called bid-ask spread. A limit order can be matched either partly or entirely. If it is not fully matched, it will remain active in the market until it is matched or cancelled (NordPool (2016b)).

- **Market order**

  Participants submit a market order when they buy or sell a certain quantity at the best available sell or buy price. Once a market order has arrived, it is matched instantly with the best available price in the order book and trade occurs.

- **Iceberg order**

  Iceberg order is a large single order that has been divided into smaller limit orders in order to hide the actual order quantity. By submitting the iceberg order just one part of it is visible until it is matched, then a new part of the hidden portion of the same size becomes visible. These smaller parts are called peak size. Therefore, for each iceberg order, a peak size and a total quantity of the order is defined. The size of the visible portion in the limit order book called the shown quantity is equal to the peak size.

  When an iceberg order is matched in a trade, its total quantity is reduced by the trade quantity. If the shown quantity before the trade was greater than the subtracted amount, the order remains visible in the market with the remaining shown quantity. If the shown quantity before the trade was less than or equal to the subtracted amount, a new slice of order quantity is made available in the market at the peak size quantity of the iceberg order. When the quantity of the last slice has been reduced to zero, the iceberg order is fully executed and removed from the order book.

  Iceberg orders can be submitted with a peak price delta. Each new slice will be entered with a new limit price which is reduced by the peak price delta for buy orders and increased by the peak price delta for sell orders.

1.1.3.3 Order execution restrictions

Some execution constraints on limit orders have been defined for continuous intraday electricity markets such as none (NON), immediate or cancel (IOC), fill or kill (FOK) and all or nothing (AON).

- **None (NON)**

  An order submitted with the execution restriction NON is either matched immediately or if it cannot be matched right away, will be added to the order book. Hence, partial order execution is allowed and they can be executed against multiple orders to create multiple trades. The default execution restriction is NON if nothing is entered in the execution restriction field.

- **Immediate or cancel (IOC)**

  The IOC execution restriction forces the order to be either matched immediately or if it cannot be matched, deleted without entering into the order book. Partial executions are allowed and IOC orders can be matched against multiple other orders to create multiple trades. These orders are never displayed in the order book.

- **Fill or Kill (FOK)**

  An order with an FOK execution restriction has to be matched immediately with its full quantity or if it cannot be matched with its entire quantity, will be deleted without entering into the order book. FOK orders can be matched against multiple other orders to create multiple trades but partial matching is not allowed. Like IOC, they are never displayed in the order book.

- **All or nothing (AON)**

  An order with an AON execution restriction has to be exactly matched against one other order with its entire quantity or enters into the order book. Partial executions are not allowed. This restriction is only used for block orders and block orders are always AON.

1.1.4 Order book creation

1.1.4.1 Timestamp

For every submitted order into the SOB, a timestamp is registered and all timestamps are sequentially allocated.

1.1.4.2 Price-time-capacity priority criteria

- Price: orders are sorted in the SOB based on their prices such that the best price is first, meaning that buy prices are sorted descendingly (highest willingness to pay is the best bid price) while sell (ask) prices are in ascending order (lowest willingness to accept is the best ask price). Orders with the same limit price are prioritized based on their timestamp such that the oldest is the first.
- Time: orders with the same limit price are prioritized based on their timestamp such that the oldest is the first.
- Capacity: orders submitted in different local trading places can be matched provided that enough capacity is available.

1.1.4.3 Cross-border trading

Trading between different market areas is called cross-border trading. As mentioned before, borders between market areas are subject to congestion. Therefore, trades only happen between market areas provided that enough transmission capacity is available.

The CMM provides ATCs between all connected market areas for SOB. If positive transmission capacity is available between two delivery areas, the orders entered in one of these delivery areas will be displayed in the local order book of the other delivery area.

Local views will be supplemented with cross-border orders if sufficient capacity is available. Conditional to the available transmission capacity, an order can be shown in several local views with different quantities. If partial matching is allowed for an order - for example, for orders without an AON execution restriction - then that order can be displayed in the local views of the other market areas with different quantities provided that available transmission capacity is smaller than their announced quantity. For orders with full matching restriction (AON execution restriction) either their full quantity is displayed in SOB or not displayed at all. After matching an order which was visible in several local views it is eliminated from all of them.

1.1.4.4 The order matching process

Order matching just occurs between a buy (or several ones) and a sell (or several ones) order and on the same product, meaning that an hourly product cannot ba matched with two 30-minute products. Moreover, for example, an hourly product for hours 19:00-20:00 cannot be matched with hourly product for hour 20:00-21:00, etc. There are two different matching processes in the current intraday market algorithm. Regular and batch matching.

1.1.4.4.1 Regular matching

The regular matching rule which follows the price-time-priority principle is that the limit price of the best sell order (entails the lowest price among all sell orders for the same product) must be lower than or equal to the limit price of the best buy order (entails the highest price among all buy orders for the same product). Then the quantity of the matched order is declined by the trade quantity. Orders with the same limit price are prioritized based on their timestamp so that the oldest is the first.

Whenever an order with a new timestamp is submitted, regular matching is triggered. An order with a new timestamp can be a newly entered order, a modified order or a reactivated order or a new slice of an iceberg order.

- **Price determination**

  By the entry of an order with a new timestamp, its price is checked with the best price of the order already existing on the other side (buy checked with sell or reverse). If it satisfies the matching rule, then the two orders will be matched at the limit price of the order that was already in the order book. For instance, if a buy order which is newly entered is matched with an existing sell order, the limit price of the sell order is set as the trade execution price.

- **Iceberg orders in regular matching**

  If a newly entered single order is matched with more than one slice of an iceberg order which was already in the order book, the price of the existing iceberg order determines the trade price and the timestamp renewal of the iceberg order during the matching process does not effect the trade execution price. Figure 1.5 shows how a new single order is matched with an iceberg order and what would be the matching prices and quantities.

  In the first top left table of Figure 1.5 three sell orders I, Z and Y are represented, where I is an iceberg order with total quantity 200 MW, peak size 50 MW, price 15€ with peak price delta equals to 1€. This means that each new slice will be entered with a new limit price which is increased by 1€. Z and Y are regular sell orders with price and quantity pair (15,25) and (16,25), respectively.

  Let's assume that a regular buy order B with price and quantity pair (99,225) just entered and can be matched

Orders in the order book:

times-tamp	name	type	b/s	qty	prc	pqty	ppd
1	I	ICB	sell	200	15€	50	1
2	Z	REG	sell	25	15€		
3	Y	REG	sell	25	16€		

Buy order is entered:

time-stamp	name	type	b/s	qty	prc	pqty	ppd
4	B	REG	buy	225	99€		

Trades

trade no.	buy order	sell order	qty	prc
1	B	I	50	15
2	B	Z	25	15
3	B	Y	25	16
4	B	I	50	16
5	B	I	50	17
6	B	I	25	18

Figure 1.5. Iceberg matching example

with the existing orders as shown in the right table of Figure 1.5. First, 50 MW of B is matched with the first slice of best available sell order I with price of 15€. Since the second slice of I will come with price 16€, this has to be wait until Z and Y are matched because both of them have lower or equal price than second slice and Y has time priority over second slice of I. Therefore, after matching B with Z and Y, second, third and fourth slices of I will be matched with B until total quantity of B is matched.

- **Unmatchable orders**

  If a newly entered order does not satisfy the matching rule and is not an IOC or FOK order, it will be added to the order book, while IOC and FOK orders (if not matched) are instantly deleted.

- **Matching against multiple orders**

  If a newly entered order can be matched, it is not necessarily matched with just a single best order on the other side of limit order book. After first matching, if the new order still has positive quantity and better price than the existing order on the other side of limit order book, it can be matched with that at a different transaction price. Hence, it is possible with multiple transactions against multiple orders that already exist in the order book. Finally, the new order is deleted if the order quantity becomes zero or if it has the IOC restriction. Otherwise, it will be added to the limit order book with its remaining quantity.

1.1.4.4.2 Batch matching

Batch matching rounds are referred to as intraday auctions, because the matching criterion has an auction-like characteristic.

Budish et al. (2014) argue that the design of markets based on a continuous limit order book (which is the predominant design for financial exchanges) has some weaknesses. Therefore, they suggest frequent batch auctions as an alternative. These auctions are uniform-price double auctions run frequently but at discrete time intervals.

The advantage of batch auctions over continuous limit order book is getting rid of the speed race and its related detrimental effects on liquidity and social welfare. In a continuous time market just having a very tiny speed advantage is enough to win the race while in a discrete time market, even in the most frequent ones, tiny speed advantages are less valuable. Moreover, by modifying the market design from continuous to discrete time the

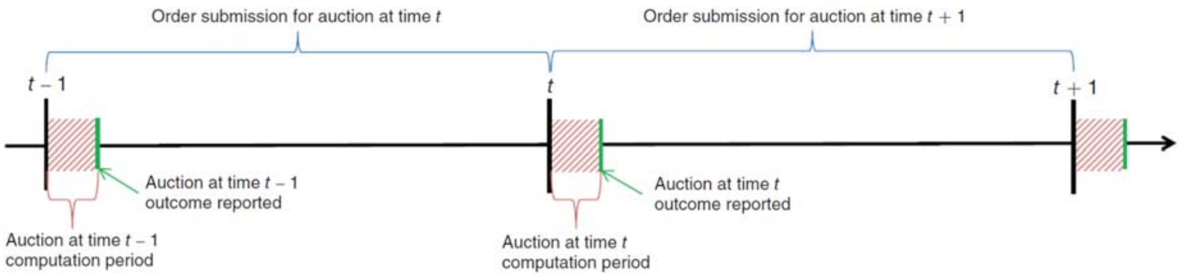

Figure 1.6. Batch matching process flow, Budish et al. (2014)

nature of competition transforms from speed to price. Budish et al. (2015) prove that these two benefits result in more liquidity and higher social welfare.

Figure 1.6 which represents the batch auction process flow is composed of 3 components: order submission, auction and reporting.

- **Order submission**

  Order submission in batch auctions is exactly similar to submission in the continuous limit order book. During the order submission time period, orders can be submitted, modified or removed. If an order is not executed in the batch auction at time t, it will automatically be transfered to the next auction at time t+1, etc., until it is either matched or cancelled.

  The main important aspect of batch auctions is that they are sealed-bid auctions, meaning that they are not displayed during the order submission time period to avoid gaming possibilities. But after running the auctions, orders are shown in aggregate at the reporting stage.

- **Auctions**

  At the end of the order submission time period, all orders are sorted ascendingly for sell and descendingly for buy and therefore, aggregate supply and demand functions will be computed. As Figure 1.7 demonstrates two cases may happen:

  1. No intersect of supply and demand functions: this case illustrates that the lowest ask price is higher than the highest bid price. Hence, no trade can occur and all orders transfer to the next batch auction.
  2. Supply and demand functions intersect: in step-wise supply and demand functions usually there is a horizontal intersection with a unique price p^* and a maximum quantity q^*. For buy orders with prices greater than p^* and sell orders with prices less than p^*, their full quantity is cleared at price p^*. For orders with price equal to p^*, one of the buy or sell orders is cleared at full quantity while for the other, only a portion of the full quantity is cleared. Therefore, the portion which is not cleared at the current auction will be automatically transferred to the next auction with time priority, meaning that orders from earlier auctions are filled first.

     Instead of a horizontal intersection, a vertical cross may also happen and this is sometimes referred to as a knife-edge situation. In contrast to the horizontal case, the quantity is uniquely determined while the midpoint of the price interval is often set as the clearing price. Since the full portion of crossed buy and sell orders are cleared, there is no need to transfer orders prorata to the next auction.

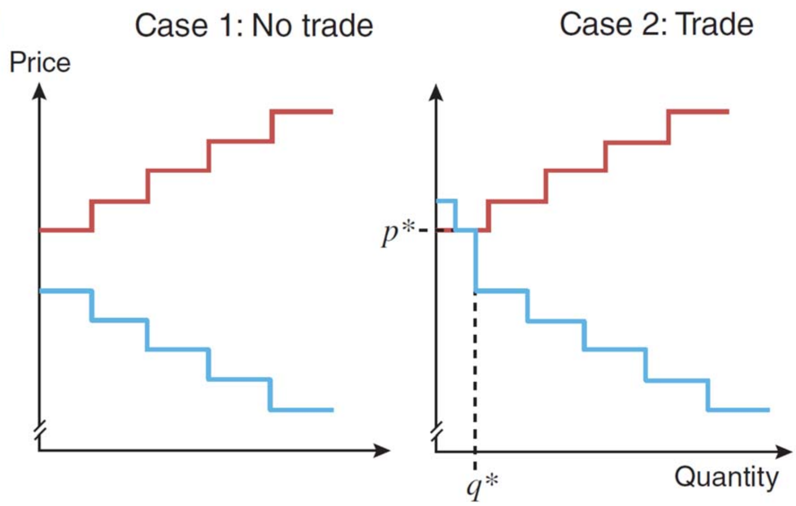

Figure 1.7. Batch auction supply and demand curves and outcome

- **Reporting**

  After clearing every single auction, the following information is announced publicly:

  – Price: the market clearing price p^* or 'no trade' outcome

  – Quantity : the cleared quantity of q^*

  – The aggregate supply and demand curves

  Moreover, the outcome of each particular order is sent to the submitter of the relevant order through a private message.

- **Duration of the Batch auctions**

  The most important and open question in designing batch auctions is to determine the duration of the batch intervals.

1.1.4.5 Trade creation

A trade is a commitment to transfer a certain amount of energy from seller to buyer at the trade price. Moreover, a trade contains information on 1- seller's and buyer's delivery areas between which the energy is transferred, 2- the paths of transferring energy, 3- the delivery period of the energy.

A trade is created whenever two orders are matched. Even in the case of multiple matching, a trade is always between exactly two orders. The order matching event comprises *price*, *quantity*, *value* and *timestamp* attributes.

The price and quantity establishment of a trade is explained in the regular matching and batch matching sections. The financial value of a trade is calculated as follows:

$$V(EUR) = Q(MW).P(EUR/MWh).d(h) \tag{1.1}$$

V: The value of the trade in Euros

Q: Quantity of the power traded in megawatt
P: The matched price of one megawatt hour energy in Euros
d: The duration of the delivery period of the trade in hours

1.1.4.6 Routing

The flow of a certain quantity of power between delivery areas may be routable via different routes. The selection of the optimal route is a deterministic process following certain rules. This process is called the routing calculation. The routing calculation is performed in two cases 1- order book recalculation 2- a trade flow calculation.

Whenever a new order is submitted in a local trading system, the SOB checks if sufficient transmission capacity is available to display the newly arrived order in the other local trading systems of the other market areas. Therefore, a change in ATC or a change in the order book content result in an order book recalculation and therefore a routing calculation.

In the case of a cross-border trade creation or cancellation, the SOB calculates the required quantity to be transferred between the source and destination areas. Then the CMM is responsible to find a routing plan which results in capacity allocations.

The XBID routing model applies the minimum cost flow routing problem principle to select the optimal routing plan. The minimum cost flow principle selects the routing plans with minimum cost among all feasible routing plans satisfying the flow constraints. In order to have a better understanding of how the XBID routing model works, an overview of the classic linear minimum cost network flow problem (MCNFP) is given.

- **Minimum cost network flow problem**

  Let's assume that the whole network which is going to be covered by XBID is a directed graph $G = (N, A)$ with n nodes (delivery areas based on the XBID definition) and m arcs (interconnectors based on the XBID definition), where N and A are the sets of delivery areas and interconnectors, respectively. Each interconnector $(i, j) \in A$, $(i, j \in N)$ has a cost c_{ij} that illustrates the unit transferring cost along the interconnector (i, j).

  Each interconnector (i, j) is also associated with a variable x_{ij} of flow on the interconnector, a lower bound L_{ij} on the flow which is the ATC_{ji} and an upper bound U_{ij} of the flow which is the ATC_{ij} in our case.

  As mentioned before, in the case of cross-border trading, when the SOB module calculates the required quantity to be transferred between source and sink delivery areas, the CMM is responsible to find a routing plan which results in a capacity allocation to interconnectors. Let's assume that $i \in N$ is a delivery area with a sell order (which is called a source node) and $j \in N$ is a delivery area with buy order (which is called a sink node) and all other delivery areas are transshipment nodes. The routing plan is responsible to find an optimal routing for quantity s_i to be transferred from delivery area i to delivery area j through a number of transfer nodes (transshipment nodes). Thus, the minimum cost network flow problem can be stated as follows:

$$
\begin{aligned}
\text{Minimize}_x \quad & \sum_{(m,n)\in A} c_{mn}x_{mn} && && (1.2a)\\
\text{subject to:} \quad & \sum_{k:(i,k)\in A} x_{ik} - \sum_{k:(k,i)\in A} x_{ki} = s_i && && (1.2b)\\
& \sum_{k:(j,k)\in A} x_{jk} - \sum_{k:(k,j)\in A} x_{kj} = -s_j && && (1.2c)\\
& \sum_{k:(m,k)\in A} x_{mk} - \sum_{k:(k,m)\in A} x_{km} = 0 && m \neq i, j \in N && (1.2d)\\
& ATC_{nm} \leqslant x_{mn} \leqslant ATC_{mn} && (m,n) \in A && (1.2e)
\end{aligned}
$$

In the above formulation constraints (1.2a)-(1.2d) are known as the flow conservation equations, while constraints of type (1.2e) are known as the flow capacity constraints.

1.1.4.7 Local view

Orders are submitted to the local trading system of each delivery area. Therefore, each local view is calculated independently. For orders submitted in different delivery areas in the same market area, all local views are the same because congestion is just enforced between market areas not delivery areas belong to the same market area.

Calculation of the local view in the local trading system, depicted in Figure 1.8, is based on the following procedure:

1. New order entered in delivery area 1 (DA1) (But it is still not visible by implicit market participant 2 in the same delivery area)

2. -A- The responsible local trading system A send the order to the SOB
   -B- The available capacity is updated by CMM and sent back to SOB. Then SOB calculates the local view of each DA and matches them if possible.

3. SOB sends the result of a new order entry to it's relevant local trading system if matching occurs, otherwise go to step 4

4. SOB sends back the local view of the new order to all local trading systems

5. All local trading systems publish the local view of the new order

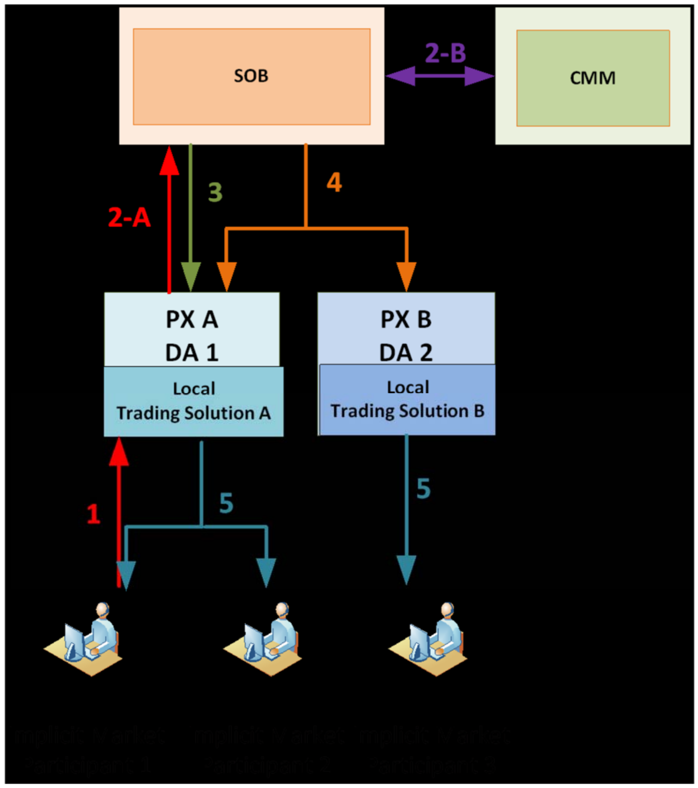

Figure 1.8. SOB. order book update (Verseille and Alaimo (2018))

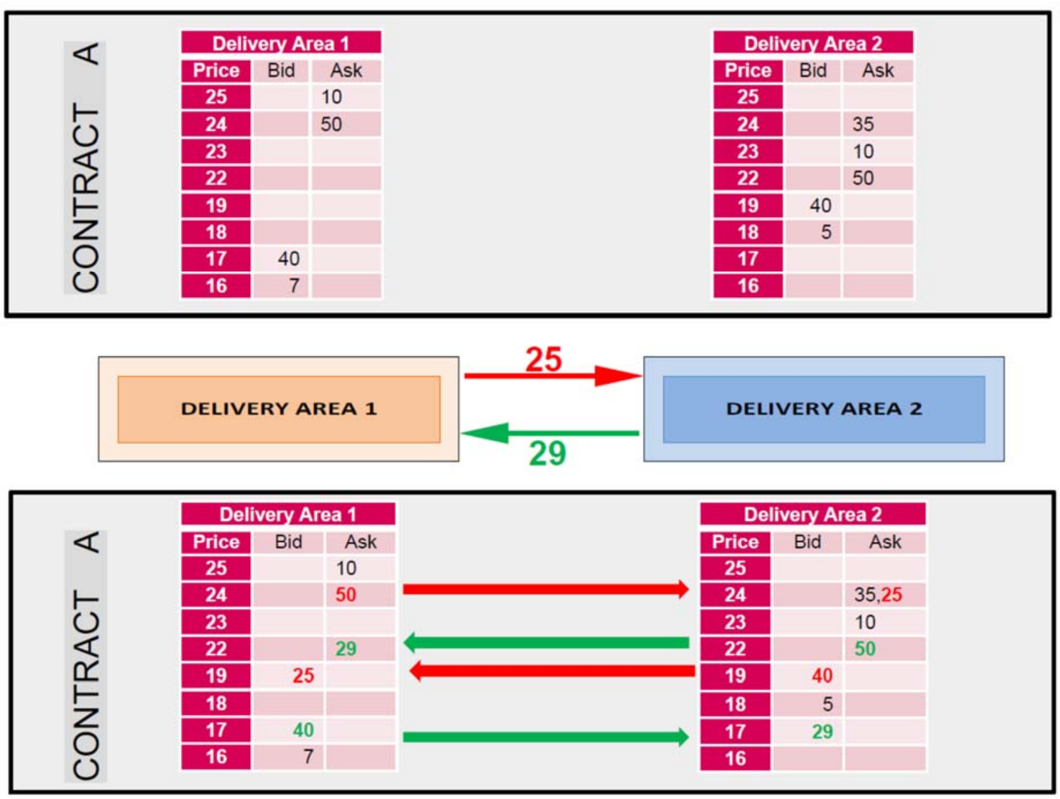

Figure 1.9. SOB. local view update based on ATC

1.1.4.8 An example of local view update

The CMM provides two ATCs for each border, one for each direction. Then for each pair of market areas the SOB calculates the maximum volume (in MW) of buy and sell orders of each market area that can be displayed in the other market area. Figure 1.9 gives an example on how to update local views based on ATCs. The ATC from DA1 (belongs to market area 1 (MA1)) to DA2 (belongs to market area 2 (MA2)) is 25 and 29 in reverse direction. The local view of orders in each delivery area for participants in the same delivery area is shown in the first table of Figure 1.9. To be more clear, participants in DA1 submitted ask orders with price and quantity pairs (25,10) and (24,50) and bid orders (17,40) and (16,7). These ask and bid orders are entirely visible for all participants in DA1 while participants in DA2 see these mentioned orders differently. It is the same for orders in DA2.

Buy orders require the flow towards the buy order delivery area. Hence, the whole quantity 40 of bid order (17,40) in DA1 cannot be shown in DA2 and just 29 out of 40 is displayed in the local view of DA2 and bid order (16,7) in DA1 is not displayed in DA2 at all. This illustrates that just 29 out of 40+7 DA1 buy bids can be shown in the DA2 local view and since (17,40) had a more attractive price it is prioritized. Sell orders require that the flow comes out of the sell order delivery area. Thus, among the sell orders (22,50), (23,10) and (24,35) in DA2, the most attractive one which is (22,50) is partially shown in DA1, with 29 out of 50.

In general, if the ATC value from MA1 to MA2 (sum of all possible routes) is a positive value X then:

- Buy orders belonging to all delivery areas of MA2 are displayed in the local view of all delivery areas of MA1 such that the maximum volume of all these external buy bids is X.
- Sell orders belong to all delivery areas of MA1 are displayed in the local view of all delivery areas of MA2 such that the maximum volume of all these external sell orders is X.

If the ATC value from MA2 to MA1 (sum of all possible routes) is a positive value Y then:

- All sell orders in all delivery areas of MA2 are visible in all DAs of MA1 such that the maximum volume of all these external sell orders is Y.
- All buy orders in all DAs of MA1 is visible in all DAs of MA2 such that the maximum volume of all these external buy orders is Y.

Finally, for cross-border trading after checking available capacity based on the mentioned approach, they will be ranked according to the price-time-priority principle. Except AON orders which have to be shown with their full submitted quantity, other orders can be displayed with a fraction of their submitted quantity.

Chapter 2

Market Power Under Nodal and Zonal Congestion Management Techniques

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Abstract

Contrary to the common thought that nodal pricing provides more opportunities for a strategic player to exert market power than the zonal model, we show that in the latter one because of the need for redispatch or counter-trading, another extra opportunity for gaming the market is created. Therefore, if proper market power mitigation approaches are not utilized in both day-ahead and redispatch markets, then zonal pricing may be more susceptible to market power. Especially in a zonal model which is based on available transfer capacity (ATC), a strategic player's profit and social welfare can be very volatile. In general, the more network constraints are incorporated in the day-ahead market (100% in nodal and almost zero in ATC), the more social welfare is attainable. Hence, the nodal model is acquitted from the more market power denunciation. This result can be generalized to the case where market power mitigation rules are just enacted on the day-ahead market. Then both the strategic player, as well as society, get the highest benefit from the nodal model. However, the zonal pricing outperforms the nodal one in the case of setting mitigation rules just on the redispatching or counter-trading stage and again nodal model is the prime suspect.

Keywords: Market design, congestion management, available transfer capacity (ATC), flow-based market coupling (FBMC), market power, flexibility cost of redispatch or counter-trading

2.1 Introduction

In designing efficient electricity markets, dealing with congestion is always a controversial issue. For many years, there was an objection to nodal pricing, that it has the more potential of exercising market power, and the argument was that due to more price areas and less producers, and therefore less competition in each node than zonal pricing, a strategic player finds more opportunities to exercise market power. Therefore, the first suggested solution is to aggregate some nodes into larger zones and hence create more competition across a wider area by limiting the power of the strategic player.

In this paper, we are examining this claim through an illustrative example. Specifically, we compare the market power potential of nodal versus zonal pricing with Available Transfer Capacity (ATC) and Flow-Based Market Coupling (FBMC), which are the dominant methods to allocate capacity to cross-border interconnections in Europe.

Electricity exchange is subject to the constraints of the transmission network. Congestion occurs when the transmission lines do not hold enough capacity to fulfill the market requirements. Therefore, congestion management (CM) techniques are deployed to dispatch an optimal power resulting from the market such that network constraints are not violated. Congestion management techniques can be categorized into five groups (Vries and Hakvoort (2002)):

1. Explicit auctions
2. Implicit auctions
3. Market splitting
4. Redispatching
5. Counter-trading

Vries and Hakvoort (2002) drew a comprehensive economic comparison among these methods based on their theoretical economic efficiency. They concluded that all these methods potentially lead to economic efficiency in the short term. However, they may result in different distribution of costs, implementation costs, openness to strategic behavior as well as the long-term incentives for generators and transmission system operators.

A state-of-the-art review of CM techniques is done by Pillay et al. (2015). They classify CM techniques into avoiding or relieving congestion methods. Besides discussions on CM methods, various optimization techniques for solving CM as well as their adaption in different countries are mentioned.

In general, various CM techniques can be distinguished by the level of integrating energy and transmission. On the one side, there is an explicit auction, with a 100% separation of energy and transmission, in which the capacity on the international interconnections (in Europe) has been auctioned in auctions separated from energy. Therefore, the prices of these two commodities are not coordinated.

On the other side, nodal pricing, which is the perfect realization of an implicit auction, fully merges energy and transmission, such that electricity prices cannot be decomposed into energy and transmission prices. Zonal pricing, which is implemented in the whole of Europe, can be considered as an intermediate implicit auction. The first stage of zonal pricing, which is the energy market, is operated by several power exchanges (PXs), each of them control some pre-defined bidding areas or price zones. These price zones are linked by "transfer capacities (TCs)"[1]between zones which are provided by transmission system operators (TSOs). Then in the second stage, depending on the market design (which can be market splitting, redispatching or counter-trading), TSOs are responsible of securely dispatching the obligations from their related energy market such that intra-zonal congestion never happens.

Though implementing the stages of zonal pricing seems straightforward, there still exists a lot of details about the collaboration among PXs as well as TSOs. The collaboration among PXs was dealt with by implementing market coupling in Europe. The initiative of price coupling of European PXs started in 2009. The aim of Price Coupling of Regions (PCR) is to develop a single price coupling solution to increase liquidity, efficiency and social welfare all through Europe EPEX-SPOT (2017). But there is still a lack of the same consensus among TSOs about how to share information with each other as well as the algorithm to be utilized.

Oggioni and Smeers (2012), Oggioni et al. (2012), and Oggioni and Smeers (2013) analyzed different versions of market coupling with respect to various degrees of coordination among TSOs. They assume that TSOs have to do counter-trading in order to reach a viable intra-zonal network solution on their control area. Therefore, they concluded that the high level of their collaboration and, more significantly, the right ATC adoption, could bring about as efficient results as the benchmark nodal pricing case. Kunz (2013) pursued the same approach as Oggioni and Smeers (2013) for the study region of Austria, Czech Republic, Germany, Poland and Slovakia. They wrapped up with the conclusion that the higher the coordination and sharing of network information, the more efficient is the market coupling.

Regardless of how zonal pricing is designed, the efficiency of it compared to nodal pricing has been debated in several papers. For instance, in Bjørndal (2000), Bjørndal and Jørnsten (2001), Bjørndal et al. (2003), Bjørndal and Jörnsten (2007), the authors argue that the problem of choosing the right number and definition of zones, makes the zonal approach a thoroughly challenging congestion management method. And it can make a great impact on the amount and distribution of surpluses among market participants and network operators.

On the other hand, zonal pricing has always been advocated by some policy makers, due to its less potential of exercising market power, with the reasoning that joining several nodes together culminate in having more competitors in each zone. Therefore, the power of each firm can be suppressed compare to the nodal pricing approach.

However, Hogan (1999) and more specifically Harvey and Hogan (2000) refute this idea by giving several illustrative examples and show that zonal pricing makes poorer incentives for investment, and socializing the higher costs to consumers, requires more administrative rules and more payments to generators for reducing production in the case of intra-zonal congestion.

Nevertheless, so far nodal pricing has mainly been objected by European politicians. For instance, the German government believes that nodal pricing could have destructive effects on market competition and liquidity (Goldthau (2016)) by saying that: "Smaller bidding areas tend to have an adverse effect on the market structure and competition on the wholesale and retail markets, because the probability of profitable exhibition of market power by incumbent market players increases."

[1]Based on the definition in Van den Bergh et al. (2016), "the Available Transfer Capacity (ATC) is calculated as the maximum commercial exchange between two market areas, compatible with the physical transmission constraints and operational security standards. In order to calculate the ATC, TSOs estimate the parallel flows that will result from the market outcome. The ATC calculation method is based on heuristic rules and day-2 estimations of the market outcome (i.e., the so-called Base case). The ATC value is determined for each cross-border link (interface) and can depend on the flow direction of the line due to the assumptions made in the ATC parameter calculation."

In order to test this assertion mentioned by many European politicians about less market power of zonal pricing, several papers were modeling redispatch or counter-trading to assess strategic behavior of generators. However, detecting strategic behavior is very difficult to prove, especially with hydro power plants, since quantifying the water value independent of energy value is practically impossible.

Holmberg et al. (2015), which is based on the notion of Nash equilibrium, compared three congestion management techniques - nodal, zonal (uniform pricing) and discriminatory (pay-as-bid)- from a game-theoretical point of view. With the assumption of perfect competition, inelastic demand and the full participation of all agents in the real-time market, they came to the conclusion that the three mentioned market designs are equally socially efficient. But in zonal pricing with redispatch, the payments from TSOs to producers is higher than nodal pricing and pay-as-bid.

There could be several reasons that make analyzing strategic behavior a very challenging task. For example, the geographical placement on the network could make an opportunity for some players to earn more profit. Furthermore, the bidding strategy analysis of a generator that has several assets on different nodes or zones is certainly different from a single one. The last but not the least is the marginal cost of a generator in its production area. Hers et al. (2009) consider four different varieties of strategic behavior in a redispatch model; locating in constrained-on or -off regions combined with price or volume bidding. Then, they test the results on the real Dutch network by the COMPETES model. They conclude that by implementing redispatch, more firms will be allowed to enter into the market in which none of them would come now because of the current situation of the market.

Dijk and Willems (2011) compare nodal pricing with counter-trading with respect to their long-term effects on entry and investment decisions, by drawing the final inference that counter-trading is an inefficient congestion management tool as well as an unproductive instrument to incentivize competition in the electricity market.

In our paper, we examine which of the three congestion management mechanisms, i.e. 'nodal pricing', 'zonal pricing with Available Transfer Capacity (ATC)', and 'zonal pricing with Flow-Based Market Coupling (FBMC)', shows the most potential for exercising market power.

As mentioned before, until 2015 zonal pricing with ATC was mainly deployed in Europe. Afterwards, zonal pricing with FBMC has been used for cross-border capacity allocation in the Central western European (CWE) day-ahead markets Van den Bergh et al. (2016). Unlike the ATC approach, FBMC considers the physical transmission constraints at the energy market clearing stage but with a different approach from the nodal pricing model.

This paper is different from previous papers in that it considers the market power under various congestion management techniques with respect to the following main aspects:

1. The arbitrage possibility between the day-ahead and real-time markets is given to the strategic generator to see if it is more profitable to behave strategically in both markets than in a one-stage nodal pricing benchmark case.

2. Zonal pricing with FBMC has not been compared by preceding congestion management methods from a market power point of view.

3. Whether and how different ATC quantities for cross-border lines affect the strategic behavior of generators. Do they result in higher or lower surpluses than the nodal benchmark case?

4. Owing to the hardship of resetting plans close to the real-time delivery, especially for inflexible generators,

the flexibility cost of production has been considered in the real-time market. It is similar to Morales et al. (2014) and Bjorndal et al. (2016) approach in respect of flexibility costs. It means that generators are capable of submitting different offers in day-ahead and real-time.

The rest of the paper is organized as follows. In Section 2.2, the mathematical models of nodal pricing, zonal pricing with ATC and zonal pricing with FBMC are described. Market power modeling is also represented in the same section. These models are tested on a numerical example explained in Section 2.3. The strategic behavior of two different generators, which are located at different nodes of the network, is studied when they play strategically just in one of the day-ahead or real-time markets or in both. Finally, conclusions are given in Section 2.4.

2.2 Model

2.2.1 Modeling assumptions

The main assumptions of the model are listed below:

1. The model represents the strategic decision of an individual strategic generator in different market designs-nodal, zonal with ATC and zonal with FBMC. All the other generators and demands are price takers, therefore, they offer their marginal cost and benefit to the market.
2. For simplicity, a single-period market has been considered but it can be extended to the multi-period case. In studying market power, especially in hydro-dominated electrical systems, inter-temporal decisions could make great differences in the profit of strategic player.
3. DC representation of the network that includes first and second Kirchhoff laws has been considered.
4. Following to EUPHEMIA algorithm (PCR (2013)), linear offer and bid curves are respectively considered for generators and consumers.
5. Any kind of uncertainties are not taken into account.
6. Nodal pricing is just one stage model because the whole physical network is modeled in day-ahead market. However, in zonal pricing, due to overlooking physical network in day-ahead, to avoid congestion, intra-zonal network constraints are considered in real-time market.

2.2.2 Notation

We adopted almost the same mathematical formulation as Bjorndal et al. (2016). The model entails I participants either generators with positive or consumers with negative values. For each $i \in I$, there exists solutions x_i and X_i for day-ahead and real-time markets respectively.

C_i^1 represents the set of feasible solutions corresponding to participant i for day-ahead market, whereas C_i^2 proportionates to the real-time market feasible solutions which is dependent on the decision x_i from the day-ahead market. Therefore, a feasible solution to both day-ahead and redispatch markets must satisfy the following constraints:

$$x_i \in C_i^1 \qquad i \in I \tag{2.1}$$

$$X_i \in C_i^2(x_i) \qquad i \in I \tag{2.2}$$

Each generator and load i locates in a specific node $n \in N$ as well as a pre-determined zone $z \in Z$. Nodes of the network are connected by a set of physical transmission lines L. Corresponds to each line l, there is a flow $f = (f_l)_{l \in L}$. If ν_0 and ν_1 show the starting and ending nodes of line l and $f_l > 0$, then it means that power is flowing from ν_0 to ν_1.

For every adjacent zones which are connected by physical connections l, there exists an inter-zonal interface $e \in E$ which conveys commercial flows between zones. Likewise the definition of f_l, corresponds to each inter-zonal interface e, there is a flow $(f_e)_{e \in E}$. If ω_0 and ω_1 show the starting and ending zones of interface e and $f_e > 0$, then it means that commercial flow is flowing from ω_0 to ω_1.

U^1 and U^2 represents network constraints in the day-ahead stage of nodal and zonal models respectively. More detailed explanation about network constraints are given in Sections 2.2.3, 2.2.4 and 2.2.5.

2.2.3 Nodal pricing

In nodal pricing method, market clearing prices are calculated for locations on the network called nodes. The nodal price composed of the marginal cost of energy plus the marginal cost of transmission which composed of loss and congestion costs. As mentioned before, these two elements can not be decomposed into two energy and transmission prices due to the implicit approach behind their calculation. The majority of US markets trade electricity on a nodal basis with very efficient market result experience (Neuhoff and Boyd (2011)). The market operator clears the market by maximizing the social welfare subject to the physical network constraints in a lossless DC approximation of the network flows. As mentioned in 2.2, consumers can be considered as generators with negative values. Therefore, their benefit curve with negative values is likewise a cost curve. Hence, the objective function can just be outlined by costs. By virtue of full network consideration in day-ahead market, just day-ahead costs are included in the objective function of nodal model.

Each offer $i \in I$ is associated with a linear day-ahead marginal cost and benefit function $a_i + b_i x_i$ with non-negative parameters a_i and b_i. To keep conciseness, we assume that inverse demand curve take negative values $x_i < 0$. Thus, the corresponding curve $a_i + b_i x_i$ has a downward slope. Accordingly, the total day-ahead cost of participant i, which is the area under marginal cost or benefit curve, is a quadratic cost or benefit function $c_i(x_i) = a_i x_i + \frac{1}{2} b_i x_i^2$.

To sum up, the mathematical formulation for nodal pricing is as follows:

$$\text{Minimize}_{x,f} \quad \sum_{i \in I} c_i(x_i) \tag{2.3}$$

subject to:

$$x_i \in C_i^1, \quad i \in I \tag{2.4}$$

$$\tau_n(f) + \sum_{i \in n} x_i = 0, \quad n \in N \tag{2.5}$$

$$\tau_n(f) = \sum_{l:\nu_1(l)=n} f_l - \sum_{l:\nu_0(l)=n} f_l, \quad n \in N \tag{2.6}$$

$$f \in U^1 \tag{2.7}$$

$\tau_n(f)$ represents the net inflow of power in node n from the network. Moreover, U^1 denotes all physical network constraints related to a DC load flow model. Consequently, (2.7) is equivalent to the following constraints:

$$f_l = Y_l.(\Theta_{\nu_1(l)} - \Theta_{\nu_0(l)}) \quad l \in L \tag{2.8}$$

$$-\,cap_l \leqslant f_l \leqslant cap_l \quad l \in L \tag{2.9}$$

$$\Theta_1 = 0 \tag{2.10}$$

(2.8) shows that flow is dependent on line characteristic parameter Y_l which is the susceptance of line l as well as phase angel Θ of related starting and ending nodes. In constraint (2.9), cap_l shows the thermal capacity of line l. Finally, By (2.10), the first node is considered as a reference node.

2.2.4 Zonal pricing with ATC

All European electricity markets except Scandinavia and Italy, were organized nationally such that each country concentrates on self-sufficiency of its electricity supply. Therefore, zonal approach was suggested by ENTSO as an electricity trading target model, to couple all these interconnected markets which are called bidding zones. So as to accomplish a global social welfare goal throughout the whole continent, the interconnection capacity among bidding zones should be considered in the trading process. But the physical transmission network creates limitations on international trade. Thus, how the available capacity for trading is calculated could have profound impact on market result and efficiency. Thus far, excluding central western European countries, the ATC mechanism is the dominant method to allocate capacity to cross-border interconnections.

ATC is related to the simplified zonal view of the transmission system in the day-ahead market and means that the Kirchhoff laws that describe the physical power flow are partially ignored in day-ahead market. The ATC calculation method is discussed in several papers; for example see Rious et al. (2008). However, the calculation of the ATC is vague and not published or informed by TSOs. To gain a maximal social welfare in the whole Europe, Jensen et al. (2017) and Aravena and Papavasiliou (2017) mentioned that ATCs should not be determined exogenously, rather should be optimized endogenously synchronized with day-ahead and real-time markets. The ATC calculation discussion is beyond the scope of our paper, but something that distinguishes this paper from former ones is how different ATC quantities for a specific inter-zonal interface $e \in E$ could encourage or discourage market power. These inter-zonal interfaces are different from physical connections l.

The day-ahead market is a pool composed of all fully coordinated power exchanges whom receives offers and bids of their related zones as well as the interface ATCs from their corresponding TSOs. The mathematical formulation for day-ahead market is as follows:

$$
\begin{aligned}
&\text{Minimize}_{x,f} && \sum_{i \in I} c_i(x_i) && && (2.11)\\
&\text{subject to:} && x_i \in C_i^1, && i \in I && (2.12)\\
& && \tau_z(f) + \sum_{i \in z} x_i = 0, && z \in Z && (2.13)\\
& && \tau_z(f) = \sum_{e:\omega_1(e)=z} f_e - \sum_{e:\omega_0(e)=z} f_e, && z \in Z && (2.14)\\
& && f \in U^2 && && (2.15)
\end{aligned}
$$

$\tau_z(f)$ declares the net inflow of power in zone z from all inter-zonal interfaces $e \in E$. Unlike nodal day-ahead market, just commercial flows which do not reflect physical network constraints are modeled in zonal day-ahead market. U^2 only shows the inter-zonal trade capacities and is equivalent to the following constraints:

$$- ATC_e \leqslant f_e \leqslant ATC_e \qquad e \in E \qquad (2.16)$$

Due to disregarding real characteristics of electrical network in day-ahead market, it is very probable that day-ahead solution does not satisfy the physical network constraints in the real-time stage. Therefore, a remedial action is invoked by TSOs to release congestion after clearing of the energy market. Based on the design and settlement methods of real-time market, several corrective actions have been explored and argued in many papers. For example, van Blijswijk and de Vries (2012) evaluates which of the three corrective mechanisms 'system redispatch', 'market splitting' and 'market redispatch' is mostly congruent with Dutch electricity transmission grid. Whereas, Oggioni and Smeers (2013) and Dijk and Willems (2011) focused on counter-trading owing to lack of the documentation of the other methods.

The aim of redispatching is finding optimal deviations from day-ahead scheduling. Hence, two re-adjustment actions should be taken to balance supply and demand in nodes connected to congested lines:

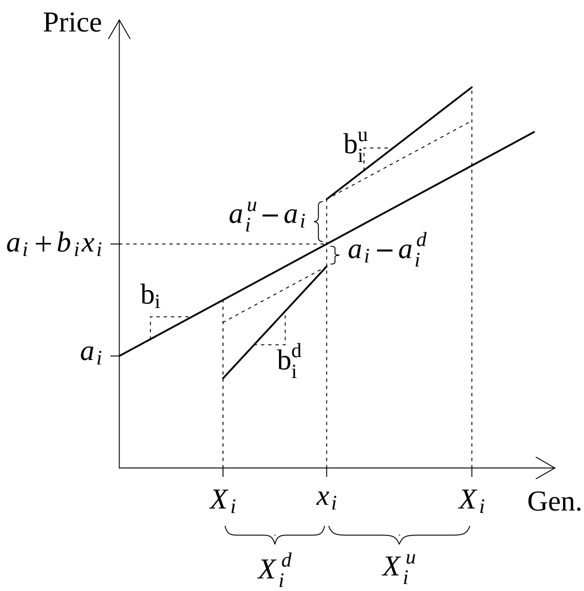
- Down-regulation: the generators in the constrained-off area (area with excess of energy) have to decrease their production by buying-back the deviated quantities from day-ahead market or consumers have to increase their consumption.
- Up-regulation: as opposed to down-regulation, the generators in the constrained-on area (area with deficit of energy) have to increase their production or consumers decrease their consumption by selling the day-ahead market contracted electricity they decided not to use.

But changing the plan of the system (which was arranged in day-ahead) in a time-interval close to the delivery hour, requires flexible sources. This flexibility can originate from various sources like energy storage, demand-side management, etc. Another essential source of flexibility is conventional generators' ability to change their output to follow varying load. The ability of changing production in a short interval depends on technological aspects such as minimum up/down times, ramp rates, minimum generation levels and start-up costs (Palchak and Denholm (2014)) whereby some additional costs will be enforced to generators as well as the system.

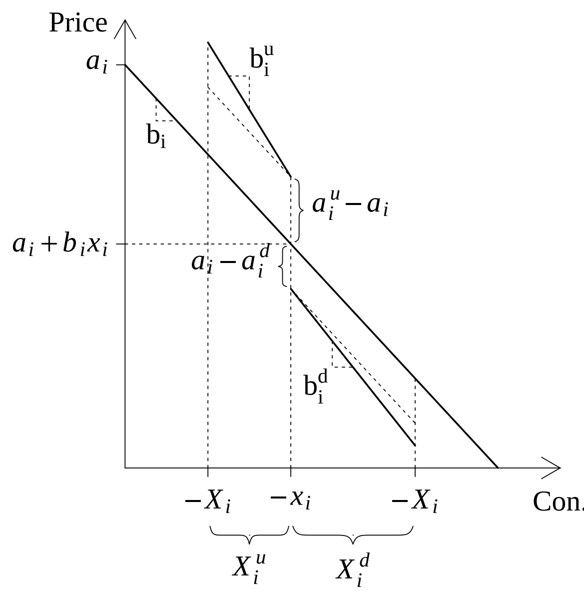
Hentschel et al. (2016) evaluate the monetary value of conventional power plant flexibility options through developing a valuation tool which relates a change in technical parameters to an economic effect and revenue. Therefore, generators and consumers can have a different cost and benefit curve (offer/bid curve) in real-time ascribed to flexibility costs. If in real-time the generators are asked to increase their production beyond the day-ahead level, then flexibility cost means that the cost of generation is higher than the day-ahead marginal cost. If they reduce production from the day-ahead level, then they have to repurchase this deviated quantity which is less valuable than their day-ahead marginal cost. On the opposite side, if the consumers increase their consumption in real-time, their bid will be lower than in day-ahead, because it is not as valuable as if it was planned in day-ahead and if they reduce their consumption, they are eager to be compensated by asking higher than their day-ahead willingness to pay.

The relation between day-ahead and real-time cost and benefit functions is shown in Figure 2.1. The left-handside figure represents an offer (supply) curve for a generator, while the bid (demand) curve of a consumer is illustrated on the right-handside. Moreover, the real-time flexibility costs in the case of deviation from day-ahead market is shown in both figures.

Flexibility costs results in different cost and benefit function parameters in redispatch stage. If $i \in I$ is a generator, then parameters a_i^u and b_i^u are used for up-regulation and a_i^d and b_i^d for down-regulation where $a_i^d \leqslant a_i \leqslant a_i^u$ and $min\{b_i^u, b_i^d\} \geqslant b_i$. For the demand-side, flexibility parameters look similar.



(a) Supply function for a specific generator



(b) Demand function for a specific consumer

Figure 2.1. Supply and demand functions for a specific generator and consumer offers/bids to the day-ahead market plus the flexibility costs incurred in real-time

With respect to Figure 2.1, redispatch model is as follows:

$$\text{Minimize}_{X_i^u, X_i^d, F} \quad \sum_{i \in I} c_i(X_i) + \tilde{c}_i(x_i, X_i) \tag{2.17}$$

$$\text{subject to:} \quad X_i \in C_i^2(x_i), \qquad i \in I \tag{2.18}$$

$$\tau_n(F) + \sum_{i \in n} x_i + \sum_{i \in n} X_i^u - \sum_{i \in n} X_i^d = 0, \qquad n \in N \tag{2.19}$$

$$\tau_n(F) = \sum_{l:\nu_1(l)=n} f_l - \sum_{l:\nu_0(l)=n} f_l, \qquad n \in N \tag{2.20}$$

$$F \in U^1 \tag{2.21}$$

In (2.17), $\tilde{c}_i(x_i, X_i)$ illustrates the additional cost caused by flexibility in the redispatch market. The flexibility cost is dependent on the day-ahead quantity x_i as well as the revised quantity X_i after running the redispatch and is constructed as follows:

$$\tilde{c}_i(x_i, X_i) = (a_i^u - a_i)X_i^u + 0.5(b_i^u - b_i)(X_i^u)^2 + (a_i - a_i^d)X_i^d + 0.5(b_i^d - b_i)(X_i^d)^2 \tag{2.22}$$

Where $X_i^u = \max\{X_i - x_i, 0\}$ and $X_i^d = \max\{x_i - X_i, 0\}$. Further examples and discussions are provided in Bjorndal et al. (2016).

Definition of $\tau_n(F)$ and U^1 are the same as nodal model mentioned in Section 2.2.3. However, F illustrates the physical flow in redispatch model. It should be noticed that in balancing constraint (2.19), x_i is fixed from day-ahead market result. Hence, just readjustments X_i^u and X_i^d will be optimized such that all physical network flows are satisfied.

2.2.5 Zonal pricing with FBMC

Several years experience of running European electricity market with the conventional ATC mechanism reflects the necessity of incorporating the physical properties of the power network into the market/clearing stage. So, including network properties into the market is the basic idea behind flow-based market coupling (FBMC), distinguishing it from ATC model.

Similar to the ATC model, FBMC entails three main steps: 1- pre-market coupling which provides required parameters by respected TSOs, 2- market coupling which is clearing day-ahead market, 3- post-market coupling by counter-trading. The detailed explanation of each step is as follows: At the pre-market coupling step, which is called the preparatory phase and starts D-2 before delivery time, TSOs are responsible of publishing all required parameters of FBMC:

- Generation shift keys (GSK) and zonal power transfer distribution (PTDF) factors: GSKs transform the nodal PTDFs into zonal PTDFs. The nodal PTDFs describe how one unit injection into a given node flows on a given line in the network. While the FBMC requires that PTDFs describe the relation between a zone and a line, means the net injections into a zone determines the flow on a particular line. Therefore, the node-to-line

PTDFs should be aggregated into the equivalent zone-to-line PTDFs. However, the result of the aggregation is very dependent on how the change in a zone's net injections is divided on the nodes within that zone. The key note here is that prior to the market clearing, this is not known. Hence, specific methods should be developed to estimate how the change in a zone's net injection will influence the different nodes within the zone. Accordingly, several GSK strategies have been developed yet. Dierstein (2017) classified GSK strategies in three different approaches:

- Flat-partitioning: allocates the same GSK factor to each node within the same zone. In this case, $GSK_n = \frac{1}{N}$, in which N is the number of nodes in the same zone as n located.
- Residual generation capacity: This method depends on installed generation capacity in each node and is derived by the ratio of nodal residual generation capacity over the same related zonal factor: $GSK_n = \frac{p_n^{max} - p_n^{min}}{\sum\limits_{n \in Z}(p_n^{max} - p_n^{min})}$
- Base-case generation: This GSK is calculated by the ratio of node generation in base-case over the same related zonal factor: $GSK_n = \frac{G_n^{BC}}{\sum\limits_{n \in Z} G_n^{BC}}$

In this paper, Flat-partitioning and base-case GSK approaches were utilized. Before running the flow-based model, the nodal pricing model is run as the base case.

More GSK strategies (eight) to implement in the Nordic power market are introduced and analyzed in Jegleim (2015). But the main question is which of these GSK strategies is the optimal one? In the optimal GSK strategy, the difference between estimated line flow (in DA market) and actual line flow (in RT market) is the least. However, so far, there is not any GSK strategy that proved to be the optimal one. Hence, GSK strategy can be a major source of imprecision in the flow-based pre-market step. Jegleim (2015) also discusses about finding good GSK strategies.

- Critical Branches (CBs) and Remaining Available Margin (RAM): In the network simplification process of FBMC, all cross-border lines and just those intra-zonal lines which are significantly affected by cross-border trades are included which are called Critical Branches (CBs).

  Then the Remaining Available Margin (RAM)is calculated by TSOs for each CB. This parameter shows the free margin of each CB that can be used as transmission capacity in DA market. Jegleim (2015) and Statnett (2016) discussed comprehensively about how to calculate this free margin.

  In the second step which is day-ahead market, likewise zonal-ATC model, after receiving required parameters from TSOs, the pool composed of fully-coordinated power exchanges runs the following mathematical model:

$$\text{Minimize}_{x,f} \quad \sum_{i \in I} c_i(x_i) \tag{2.23}$$

$$\text{subject to:} \quad x_i \in C_i^1, \qquad i \in I \tag{2.24}$$

$$\tau_z(f) + \sum_{i \in \omega^{-1}(z)} x_i = 0, \qquad z \in Z \tag{2.25}$$

$$\psi_l(f) = \sum_z ZPTDF_l^z * \tau_z(f), \qquad l \in CB \tag{2.26}$$

$$f \in U^3 \tag{2.27}$$

The same as $\tau_z(f)$ definition in Section 2.2.4, it shows the net inflow of power in zone z from all lines belong to CBs. $ZPTDF_l^z$ is also the zonal PTDF parameter given by responsible TSO. $\psi_l(f)$ is flow over critical branch l. U^3 illustrates the CBs capacity which are constrained by RAMS as follows:

$$\psi_l(f) \leqslant RAM \qquad\qquad l \in CB \tag{2.28}$$

In general, the RAMs are positive unless a CB is known to be congested before allocation. Moreover, since the RAM of a CB is only defined in one direction, then one CB must be defined for each direction.

In this paper because of a small network we are testing, all lines are considered as CBs and RAMs are simply assumed to be equal to cap_l.

Finally, in the last step which is happening in the real-time, counter-trading or redispatching must be run. Even though the FBMC had tried to model physical network, since GSK calculation is based on the prediction of the state of the electricity system at the delivery time, the flows over lines calculated at day-ahead market may not be equal to the actual line flows or even some GSKs may not result in feasible flows in RT market. Therefore, counter-trading is necessary to find optimal deviations from day-ahead results. The assumptions about the flexibility cost of counter-trading as well as the mathematical model are exactly the same as counter-trading part of Section 2.2.4. Hence, we avoid to duplicate this part.

2.2.6 Market power modeling

After the deregulation of electricity industry, generation companies submit their offers/bids to the market operator instead of revealing their real costs. Since the aim of these bidding strategies is to maximize their profit then the potential for market power exercise will be created. Market power can be defined as the ability to profitably lifting prices above marginal cost, which results in inefficiencies mainly due to suboptimal plant dispatch.

Several reasons for the existence of market power are identified (Rahman (2011)) such as:

- Transmission constraints and market fragmentation
- High degree of concentration
- Inelastic demand
- Peak demand conditions and instantaneous balancing
- Strong national incumbents
- Joint capital control of generation and transmission capacities
- Gaps in market arrangements

However, the reason of market power can be very specific to the examined market since each market has its own loopholes that can be exploited by market participants to exercise market power. In this paper the main focus is investigating the effect of market design on market power. To understand the extent of existed market power, measuring tools are needed. They can be categorized into two main classic and dynamic methods.

The first category is just measuring market concentration and the well-known metrics are the Four-firm Concentration Ratio (I4), Herfindahl Hirshman Index (HHI) and Pivotal Supplier Index (PSI). But as we mentioned earlier there would be other reasons than just market concentration. Hence, these methods are not powerful metrics to measure the existence of market power.

The second category can be divided into two ex-post analysis and equilibria modeling. In the former approach, the difference between the actual market price and marginal cost of production shows the amount of market power while in the latter one the examined market is simulated to find the equilibria, then the difference between equilibrium prices and the marginal cost of production illustrates the amount of market power.

In this paper, the ex-post analysis approach has been adopted to measure market power. However, we tailored the measuring metrics as follows:

$$S_i = x_i.\lambda_{z:i\in z} + (X_i^{up} - X_i^{dn}).\lambda_{n:i\in n} - (c_i(X_i) + \tilde{c_i}(x_i, X_i)) \tag{2.29}$$

$$SS = -(\sum_{i\in I} c_i(X_i) + \tilde{c_i}(x_i, X_i)) \tag{2.30}$$

S_i and SS respectively represent the surplus of participant i and the overall social surplus. After running both markets the shadow price of equation (2.13) shows the day-ahead market clearing price λ_z for each zone z and similarly λ_n extracted from equation (2.19) represents the redispatch market clearing price. If i is a generator, then the first and second terms in equation (2.29) are respectively the income from day-ahead and redispatch markets while the last parenthesis calculates the overall cost of production in both markets. With respect to the assumption of negative values x_i for consumers, the first two terms in equation (2.29) represents the consumer payments and the last term is its benefit from both markets. Hence, in overall, for both kind of participants surplus is a suitable term.

With the same analogy, social surplus is equal to the consumers' benefits (bids) minus generators' costs (offers). These two indexes are used to compare the market power of different players. The more the social surplus is, the more efficient is the market design.

2.3 Results and discussion

In this section we make use of a small three-node system to illustrate and compare three congestion management approaches from market power point of view.

2.3.1 Illustrative example

The three different congestion management models are compared using the three-node system depicted in Figure 2.2. This system is composed of eight conventional generators (G_1,G_2,...,G_8), three demands (D_1,...,D_3) and three lines (L_{12},L_{13},L_{23}). All three demands are assumed to be elastic. Data related to the whole system is shown in Table 2.1.

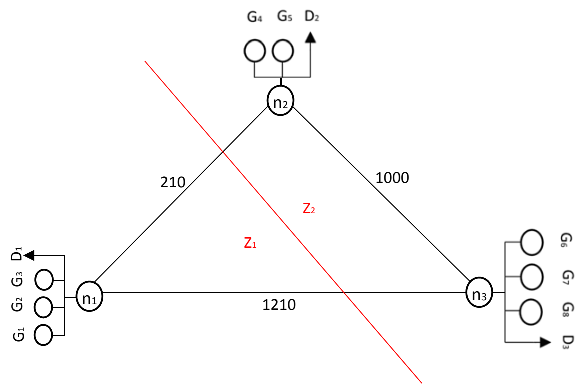


Figure 2.2. Three-bus power system

Table 2.1. Data-Three bus system

Day-ahead market			Network	
Node	Supply	Demand	Line	Capacity
1	a_{G_1}=0 , b_{G_1}=0.01 a_{G_2}=0 , b_{G_2}=0.05 a_{G_3}=0 , b_{G_3}=0.06	a_{D_1}=3000 b_{D_1}=0.3	1-2	210
2	a_{G_4}=0 , b_{G_4}=0.05 a_{G_5}=0 , b_{G_5}=0.05	a_{D_2}=3000 b_{D_2}=1.2	1-3	1210
3	a_{G_6}=0 , b_{G_6}=0.02 a_{G_7}=0 , b_{G_7}=0.2 a_{G_8}=0 , b_{G_8}=0.15	a_{D_3}=3000 b_{D_3}=0.24	2-3	1000

Real-time market		
Up/Dn	Actor	Coefficient
up-regulation	generator consumer	$\gamma^{up}_{G_i} * b_{G_i}$ $\gamma^{up}_{D_j} * b_{D_j}$
dn-regulation	generator consumer	$\gamma^{dn}_{G_i} * b_{G_i}$ $\gamma^{dn}_{D_j} * b_{D_j}$

b_{G_i} represents the slope of G_i's marginal cost function and a_{D_j} and b_{D_j} are respectively the intercept and slope of D_j's marginal benefit function.

As you can see in supply column, G_1 is the cheapest generator in n_1 as well as the whole system and G_6 is the cheapest in Z_2 and the second cheapest in the whole system while D_3 is the most expensive demand in the network. All lines have the same reactance equal to one.

The last column in RT market illustrates that for up- and dn-regulation, costs and benefits are connected to day-ahead related ones by multipliers $\gamma^{up}_{G_i}$, $\gamma^{dn}_{G_i}$, $\gamma^{up}_{D_j}$, $\gamma^{dn}_{D_j}$ where a value of 1 indicates that the redispatch costs and benefits are equal to the day-ahead ones, while higher values indicate extra costs of redispatch. In all cases of this paper, it is assumed that $\gamma^{up}_{G_i}$=$\gamma^{dn}_{G_i}$=2 and $\gamma^{up}_{D_j}$=$\gamma^{dn}_{D_j}$=1.5. It means that both marginal cost and benefit functions in RT market entail steeper slope than DA market which shows the higher costs and benefits of redispatching.

It is assumed that all generators and demands in the illustrative example are flexible enough to participate in RT market.

As we mentioned before, congested transmission network can result in market power and some generators can take advantage of their geographic location and transmission capacity constraints to exercise market power. Therefore, to test the effect of this item on market power, the results will be examined by choosing distinct strategic players on different nodes.

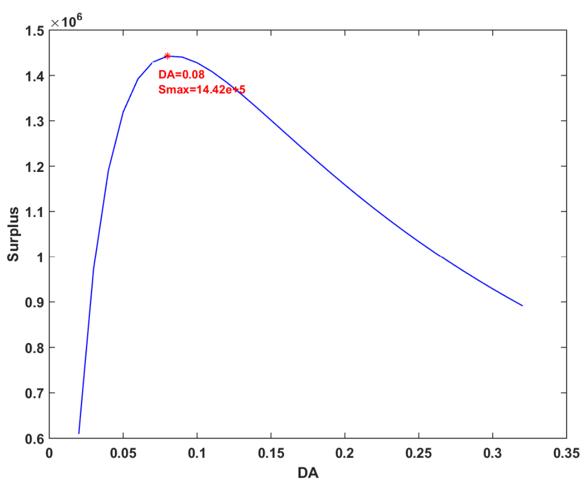
We assume that all generators except one and all consumers are price-taker participants, which means that they all submit their true costs and benefits as represented in Table 2.1. Hence, just one strategic generator can be price-maker - sets manipulated energy prices which are far from its marginal cost. G_6 in Z_2 (n_3) is assumed to be the strategic player and the results for each pricing mechanism will be demonstrated in the following subsections.

2.3.2 Strategic bidding of G_6 when plays strategically in both day-ahead and real-time markets

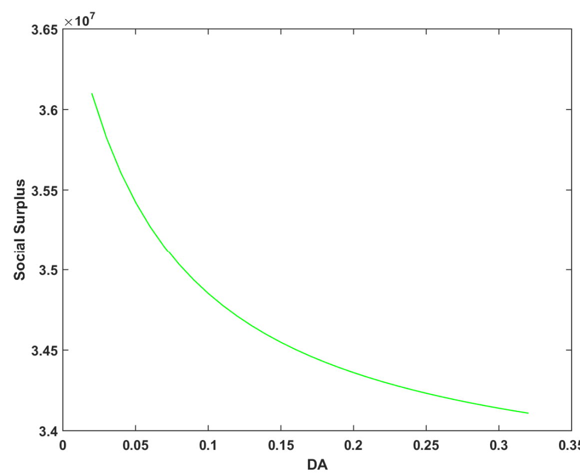
In this section we assume that G_6, owing to its size, location and flexibility is able to submit strategic bids that will increase its profit. In the following sections, the effect of market structure on its market power will be investigated.

2.3.2.1 Strategic bidding of G_6 in the Nodal model

Given the bids of the other participants are consistent with their true costs and benefits, G_6 submits a strategic bid to DA market in order to maximize its surplus. The G_6's true cost coefficient is 0.02 which results in the lowest surplus for it, while the social surplus is at the highest level. By varying this bid, G_6 can reach to the highest surplus of $14.42 * 10^5$ for DA offer equals to 0.08 (58% rises), where the corresponding social surplus is $35.033 * 10^6$ (3% reduction). From the social surplus point of view, offering true cost is the most efficient option. G_6's surplus and social surplus of the system in case that G_6 is the strategic player are depicted in Figure 2.3. The decreasing social surplus curve demonstrates the detrimental effects of market power in nodal pricing model.



(a) G_6 surplus



(b) Social surplus

Figure 2.3. Nodal pricing results

2.3.2.2 Strategic bidding of G_6 in the zonal-ATC model

Regardless of the fact that how TSOs are picking out ATCs, it is interesting to see how strategic players can benefit from irrelevant ATCs. Therefore, the results will be inspected for two end points 0 and 10000 (infinite).

2.3.2.2.1 ATC=0

Means that DA market is running for two seperate (detached) markets and balancing individual supply and demand in each zone Z_1 and Z_2. Z_1 which contains the cheapest generator G_1, clears with much lower zonal price 71 compared to 235 in Z_2 which contains the most expensive demand D_3. Hence, generators in Z_1 are eager to export to Z_2 to increase the price in their related zone.

In RT market, due to the existence of lines L_{12} and L_{13}, they find this opportunity to sell to consumers in Z_2. Hence, as you can see in Figure 2.4, all generators in n_1 do up-regulation. Since in DA market, L_{23} was neglected and D_3 is the most expensive consumption, generators in n_2 produce as much as they can but in RT market, due to the limited capacity of L_{23}, they have to do dn-regulation. In opposite, although G_7 and G_8 in n_3 are the most expensive ones, they have to do up-regulation in order to satisfy very high demand of D_3 from DA which is 11520. Thus, this expensive up-regulation in n_3 results in very high RT clearing price 545 versus very low price -71 in n_2.

But what can G_6 do as an strategic player? Based on Figure 2.5 and with respect to the fact that G_6 can submit different offers for up- and dn-regulation than DA, its optimal strategy is (DA,up,dn)=(0.14,0.14,whatever). Since G_6 is the second cheapest generator in the system and is located in the same node as D_3 (most expensive demand), it seems that it is always profitable for it to do up-regulation. Thus, dn-regulation offers are not the matter of importance in this case. In Figure 2.5(b), up and DA coordinates are replaced by each other in order to show that for the lowest DA offer 0.02, the surplus of G_6 is the lowest while the social surplus is the highest, which shows the negative correlation between its surplus and social surplus irrespective of up- and dn-regulation offers.

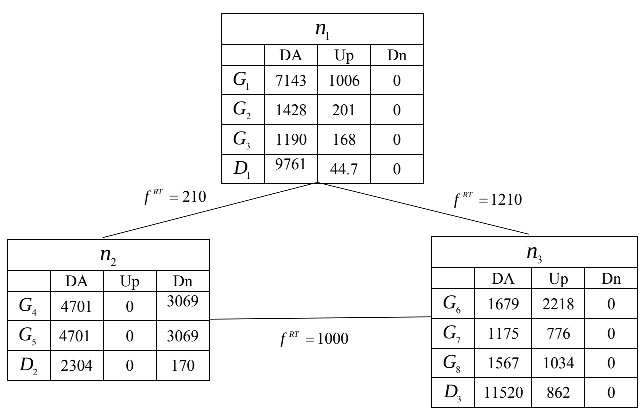
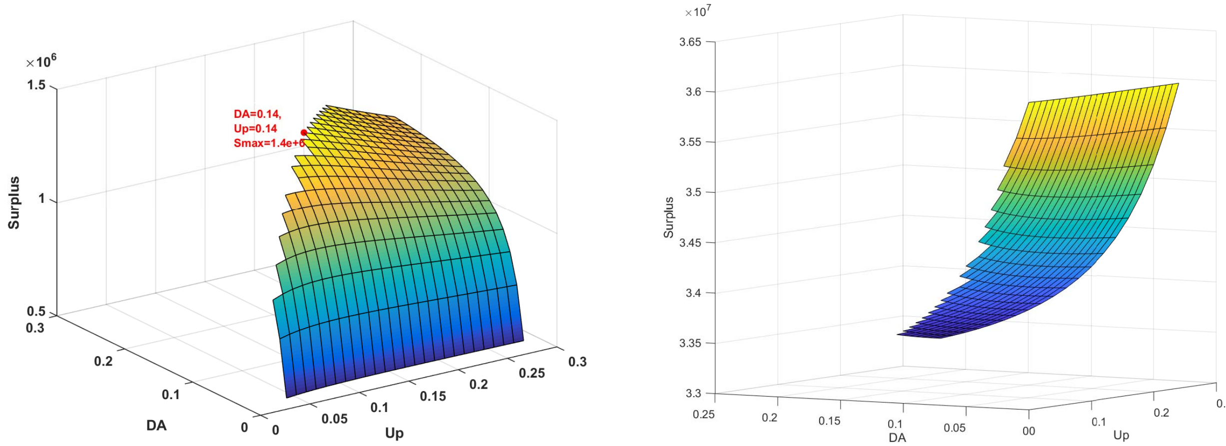


Figure 2.4. DA and RT quantities when ATC=0



(a) G_6 surplus (b) Social surplus

Figure 2.5. Zonal results with ATC=0

2.3.2.2.2 ATC=10000

Concerning the line capacities, ATC equal to 10000 can be considered as infinite transfer capacity between two zones in DA. Therefore, DA market is equivalent to the uniform pricing model and equal prices of the two zones confirm this assumption (Table 2.2). Thus, in DA market all generators located in n_1 and n_2 sell as much as they can to D_3.

But in RT, they have to come up against physical network constraints. Hence, all of them have to dn-regulate in favor of generators in n_3. By playing strategically, G_6's best offer is (DA,up,dn)=(0.17,0.17,whatever). Identical to ATC=0 and Figure 2.5, for the lowest DA offer equals to 0.02, G_6's surplus is at minimum level while social surplus is maximum.

Table 2.2. Zonal and nodal prices for ATC=10000

$\lambda_{Z_1}^{DA}$	$\lambda_{Z_2}^{DA}$	$\lambda_{n_1}^{RT}$	$\lambda_{n_2}^{RT}$	$\lambda_{n_3}^{RT}$
123.4	123.4	40.4	38.3	648.5

2.3.2.3 Strategic bidding of G_6 in the zonal-FBMC model

2.3.2.3.1 Flow-based market coupling with weighted-GSK

Based on the definition of weighted-GSK in Section 2.2.5, GSK is calculated based on the weight of the net injection of each node over sum of the net injections of all nodes in the corresponding zone. These net injections are based on nodal results. Nodal and zonal PTDFs corresponding to the optimal offer (DA,up,dn)=(0.15,0.15,whatever) are demonstrated in Tables 2.3 and 2.4.

Table 2.3. Nodal PTDF

Line	n_1	n_2	n_3
$1-2$	0.33	-0.33	0
$1-3$	0.66	0.33	0
$2-3$	0.33	0.66	0

Table 2.4. Zonal PTDF

Line	Z_1	Z_2
1-2	0.33	0.185
1-3	0.66	-0.185
2-3	0.33	-0.371

Similar to the zonal-ATC model, when redispatch was solved by nodal PTDFs, which shows the real network constraints, by up-regulating until 2385, G_6 can maximize its profit. Therefore, DA as well as up-regulation offers are important for it.

Different zonal PTDF calculation approaches mentioned here can result in very unexpected prices and quantities.

2.3.2.4 Discussion on market power potential of G_6

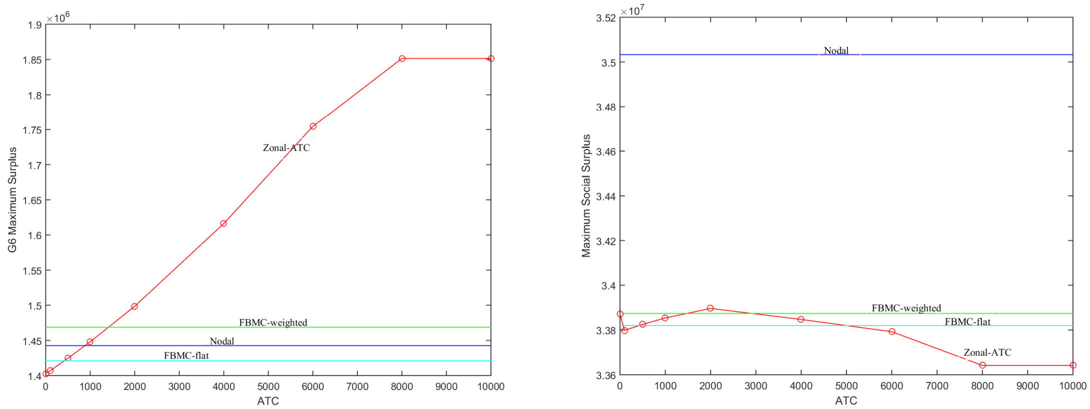
The maximum attainable surplus and social surplus from all investigated models in this paper when G_6 plays strategically is shown in Figure 2.6.

Based on the participants behavior analyzed in Sections 2.3.2.1, 2.3.2.2 and 2.3.2.3, by increasing ATC from 0 to 10000, G_6's surplus has a great increase from 1,402,703 to 1,851,429 (almost 25%). The main reason is that G_1 which is the cheapest generator is located in Z_1. Moreover, D_3, the most expensive demand is located in the same node as G_6 is located. Therefore, increased ATC lets G_1 to produce as much as it can in day-ahead market as well as generators in n_2 (G_4 and G_5) to produce without considering physical network constraints. Hence, all these conditions let the second cheapest strategic player G_6, to profitably utilize the non-feasibility of flows resulted from day-ahead market by playing with its day-ahead and real-time offers. Thus, the best offering strategy for G_6 when ATC is rising, is to shift some part of its production from day-ahead to real-time. Even though, by increasing ATC, the G_6's surplus will rise up to 25%, the maximum variation of social surplus is just 0.8% which is not considerable. By comparing G_6's surplus of nodal versus zonal-ATC model, the highest surplus it can get from nodal model is $14.42 * 10^5$ while by increasing ATC, its surplus can reach to $18.5 * 10^5$, which shows the sensitivity of the market power to ATC quantities. However, for very low ATCs, its market power is lower than nodal model.

Alike to the zonal-ATC model, FBMC with weighted GSK has the more potential of market power but not as high as zonal-ATC.

Figure 2.6 illustrates a huge difference between nodal social surplus versus the other ones. It seems that FBMC with weighted GSK leads to a more efficient market design in comparison to the other zonal models. However, if a correct ATC quantity has been chosen by TSOs, Then zonal-ATC can be as efficient as FBMC with weighted GSK.

Even though the FBMC with flat-partitioning GSK leads to the least surplus for G_6, but still the social surplus is also the lowest in comparison to the other methods, which can be justified as an inefficient market design.



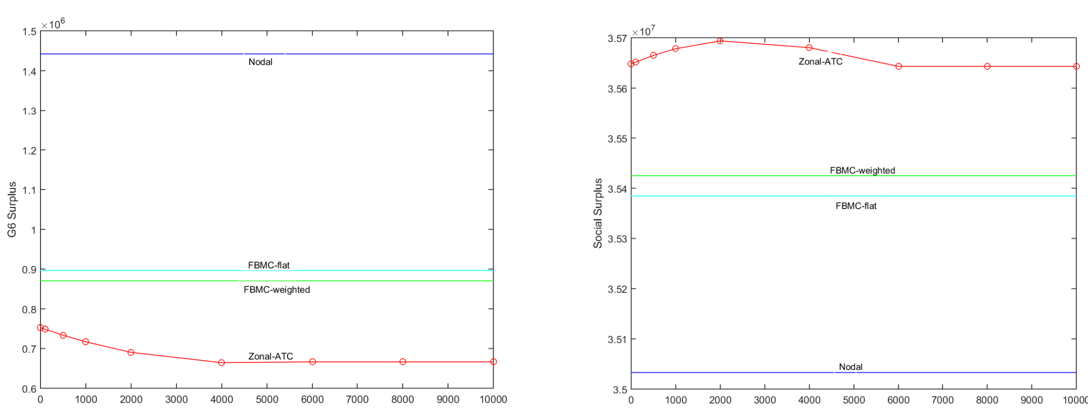
(a) Maximum attainable surplus for G_6 (b) Maximum attainable Social surplus

Figure 2.6. Maximum surplus from all models

2.3.3 Strategic bidding of G_6 when plays strategically just in day-ahead market

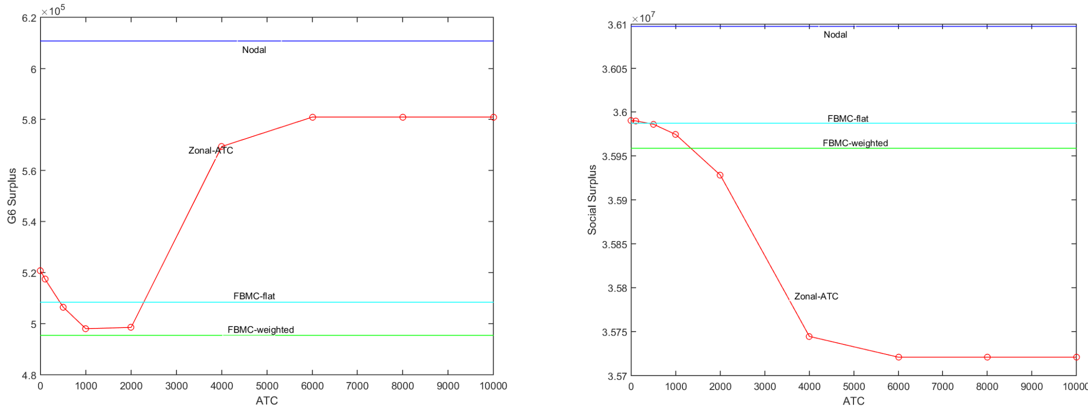
The order of the maximum attainable surplus for G_6 from all models when it just plays strategically in DA market is as follows: Nodal>FBMC-flat>FBMC-weighted>Zonal-ATC. It is obvious that since in the nodal model it considers all network constraints at the time of decision making and plays strategically with full knowledge about it, G_6 can earn the highest surplus.

In general, the more network information is considered at the time of strategic decision making (which is DA market in this case), the more potential exists for strategic player to exercise market power (Figure 2.7(a)). Therefore, nodal model leads to the lowest social surplus. In zonal-ATC model, no matter what ATC is, since it does not reflect real network constraints in DA stage, it does not result in huge profit for G_6. Finally, since in FBMC models, they are in between of nodal and zonal-ATC with respect to considering network constraints, they are placing in the middle of ranking.



(a) Maximum attainable surplus for G_6 (b) Maximum attainable Social surplus

Figure 2.7. Maximum surplus from all models when G_6 plays strategically just in DA market



(a) Maximum attainable surplus for G_6 (b) Maximum attainable Social surplus

Figure 2.8. Maximum surplus from all models when G_6 plays strategically just in RT market

2.3.4 Strategic bidding of G_6 when plays strategically just in real-time market

The figures and numbers show that having possibility to just exercise market power in real-time leads to much lower profits for G_6 in comparison to the cases where it plays strategically just in day-ahead or both markets. In contrast, social surplus is the highest, especially with nodal model. In zonal-ATC model, choosing very high ATC culminates in very low social surplus, because it signifies a very different solution of day-ahead than real-time, therefore G_6 finds more opportunity to play with its offers in real-time.

2.4 Conclusion

Several reasons have been mentioned for market power existance such as market structure, market rules, geographical concentration, congested network and so on Song (2003).

Market structure can be an important cause of exercising market power, for example which pricing machanism is implied (pay-as-bid or market-clearing-price), how future or forward contracts are designed, demand participation in market or not, etc.

In this paper we investigated the common objection -usually is mentioned by European politicians- to the nodal pricing which inherently entails more potential of market power than zonal pricing. But since in zonal pricing, either with ATC or FBMC, redispatch is necessary to achieve a feasible flow, the market power possibility should be probed in both markets. Therefore, for zonal market structure, three following cases of gaming are allowed to the strategic player:

- **Strategic behaviour in both day-ahead and redispatch**: in this case, strategic player takes an optimal decision by knowing that market is just running with simplified network or cross-border constraints at day-ahead stage, then it finds another new opportunity in redispatch market to fix its first stage decision by new offering based on real-time flexibility cost of redispatch. Therefore, in comparison to one stage gaming possibility of nodal model, the latter pricing approach surpasses the former one. In general, we can conclude that the more network constraints are incorporated in day-ahead market, the less opportunity has the strategic player to change its decision in redispatch stage. Therefore, The nodal and FBMC are less susceptible to market power than ATC model. However, in the ATC model, if right ATCs are adopted, it can be as efficient as FBMC with weighted GSK. Otherwise, particularly for very high ATCs (result in uniform pricing) or very low ones (result in detached markets), it entails the lowest social surpluses.

- **Strategic behavior in day-ahead and non-strategic in redispatch**: in this case, if the redispatch market does not allow the strategic behavior, then the strategic player can play very blindly in day-ahead when nothing about network is considered and does not have another opportunity to fix the decision taken in the previous stage. Therefore, by this assumption, both ATC and FBMC outperform nodal model.
- **Non-strategic behavior in day-ahead and strategic in redispatch**: since in this case strategic behavior is not allowed in day-ahead stage and redispatch is just based on deviations from day-ahead, strategic player finds very little space to maneuver. Therefore, this case entails the highest social surpluses in all nodal, ATC and FBMC models.

Hence, it is important to do extensive investigation about market power mitigation approaches especially in zonal models which entail two stages of incorporating network. Singh (1999) and Hogan and Newton (2001) discuss about some mitigating market power approaches which is mostly suitable for one-stage nodal model. Thus, further market power mitigation studies for zonal models can be a very interesting topic for future research.

Chapter 3

Can the European Intraday Market be Designed as a Congestion Management Tool?

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Abstract

The growth in intermittent renewable power in Europe has increased the need to trade closer to real-time. In recent years, intraday markets have been integrated across Europe, contributing to a more efficient market. On the other hand, European day-ahead and intraday markets are still based on zonal pricing, where the physical characteristics of transmission networks are only partly taken into account, and congestion problems may remain until close to real-time. In this paper, we suggest an intraday market design based on the coordinated multilateral trade (CMT) approach, using power transfer distribution factors and other network information provided by the transmission system operators, to generate profitable, but feasible, and possibly multilateral trades based on nodal bids. Profitable trades can be found by independent brokers or by having the power exchange running frequent batch auctions at discrete-time intervals. Each trade is accepted by the TSO if no violation occurs in the network, or is curtailed. If the network flow is feasible at the start of the intraday market, the procedure converges to the optimal economic dispatch. In any case, this suggestion for intraday trading, taking into account simple information about network constraints, in a procedure consistent with the functioning of the European intraday market, can help bridge the gap between the zonal day-ahead markets and the real-time constraints of the power system.

Keywords: Coordinated Multilateral Trades (CMT), Congestion management, Integrated Intraday market, Renewable integration

3.1 Introduction

The growth of intermittent generation capacity in today's electricity markets has increased the importance of efficient intraday markets, seeing that it becomes more challenging for market participants to be in balance between the day-ahead and real-time balancing markets. As investigated by many authors, an intraday market, if properly designed, can be an effective market mechanism not only for facilitating the large-scale integration of wind power generation but also for increasing wind power generators' competitiveness (Weber (2010), Mauritzen (2015), and Jafari et al. (2014)). Hence, there will be an increasing interest in trading in the intraday markets. It is beneficial both for market participants and for the power system that the network is in balance close to the delivery time, in order to reduce the need for reserves and associated costs. In this regard, the European Commission established a target model to integrate all intraday markets based on continuous trading, and XBID (cross-border intraday) was launched to create a joint integrated intraday cross-zonal market. As stated in XBID documents, the main goals of integration are to promote effective competition and pricing, to increase liquidity and to enable a more efficient utilization of generation resources across Europe.

Currently, two different exchange-based forms of intraday markets have been designed in Europe: auction-based (discrete auctions) and continuous trading intraday markets. In continuous trading, the power exchange provides a 'limit order book'-based platform wherein market participants can submit bid (for buy) and ask (for sell) orders. Whenever they find it profitable in a period between intraday market opening until minutes before delivery time, a trade occurs when the bid price is higher than or equal to the ask price. Hence, each trade has its own specific price, and this property substantially differentiates continuous trading from discrete auctions (with unique market clearing prices) (NordPool (2016b)).

The advantages and disadvantages of discrete auction versus continuous trading intraday markets have been debated in many papers. As continuous trading allows trading 24 hours/7 days a week, market participants may find an immediate opportunity to trade their imbalances. Thus, as soon as new information is received (either their own situation, like updated wind power forecasts, or signals from others that can be reflected in a bid-ask spread), it can be used immediately, and this may be especially attractive for intermittent generators (Henriot (2012b)). Conversely, Hagemann (2013b) points out that in a discrete auction intraday market, market participants have to wait until the next auction is cleared, and cannot do immediate self-balancing. Hence, continuous trading is superior to discrete auctions from an ease of trade point of view.

By simulating the behaviour of a zero-intelligent trader, Weber and Schröder (2011) assess the efficiency of continuous trading versus discrete auctions. They conclude that since continuous trading adhere to the first-come-first-serve principle, it entails a lower allocative efficiency, meaning that depending on the order arrivals, some trades with negative welfare contribution may occur while others with positive welfare contribution may never happen. This will not be the case for discrete auction markets, where the objective function is to maximize social welfare.

Scharff and Amelin (2016) empirically analysed the trading behaviour on the Elbas intraday market. Their study shows that factors like high share of wind power in Denmark, restricted available transmission capacity from Norway to continental Europe for the intraday market, and high balancing prices in Finland result in varying trading behaviour in different price zones. They also illustrate that half of the Elbas intraday trades are settled 3 hours before delivery time, most likely by wind power producers with short forecast horizon. Finally, it was concluded that since most of the intraday trades are motivated by intermittent power producers rather than by conventional power plant outages, continuous trading seems to be a more suitable design for European intraday markets.

The question of which intraday market design, continuous trading or discrete auction, is more suitable for an integrated European intraday market, is further addressed by Neuhoff et al. (2016b). They empirically assess the effect of an additional intraday auction, introduced by EPEX in December 2014. This uniform price auction is settled at the beginning of the continuous intraday session at 3 pm, for the next 96 quarters of the following day. Their observation is that adding an auction to the current continuous market increased liquidity and market depth, reduced price volatility, and removed the speed race (i.e. the race to be the first to be processed, which is an important issue in continuous trading). However, too infrequent auctions may lead to postponed adjustments, and hence, the right frequency of intraday auctions is raised as an important design question. Moreover, they conclude that with auctions, intraday transmission capacity can be allocated more efficiently, and the value of the scarce capacity can be signalled, while this is not the case for continuous trading. In the end, to reach all the above mentioned benefits, they suggest to substitute continuous trading for frequent batch auctions.

The frequent batch auction idea and its advantages over the continuous limit order book in financial exchanges, was first discussed by Budish et al. (2014) and later extended by Budish et al. (2015). Based on their definition, frequent batch auctions are identical to the continuous limit order book with two exceptions: 1. time is considered as discrete, not continuous, and 2. instead of serial processing of orders, based on their time-price priority, orders are processed in batch form using a uniform-price auction. By modifying the market in this way, the speed race is eliminated, and instead of competing on speed, price is rivaled.

In line with Neuhoff et al. (2016b), we argue in this paper that the bilateral trading structure of the continuous European intraday market does not allow efficient congestion management. Together with the simplified network models of the day-ahead and intraday markets, this create inefficiencies, which result in higher imbalance costs compared to the case where all transmission network constraints are considered in one or more markets prior to real-time. In this paper, we suggest to use the coordinated multilateral trade (CMT) approach, proposed by Wu and Varaiya (1999), to the current European intraday market in order to fix both the aforementioned sources of inefficiency. The CMT approach allows multilateral trades (instead of just bilateral trades) which are necessary to relieve congestion. Moreover, by replacing the information transferred between transmission system operators (TSOs) and power exchanges from available transmission capacities of cross border interconnectors (which are imaginary lines between zones) to power transfer distribution factors (ptdfs) of congested lines (which are physical lines between nodes), the intraday market can reach to the optimal economic dispatch. In this paper, we focus on congestion issues, and not other sources of imbalances or flexibility costs, so we assume that supply and demand functions remain fixed throughout the day-ahead and intraday markets, and no uncertainty is modeled.

The rest of the paper is organized as follows. In Section 3.2, we review different congestion management approaches which are equivalent to the optimal economic dispatch and optimal nodal pricing model. This literature review is needed to understand the relationship between the current European design, the CMT approach, and optimal economic dispatch. Section 3.3 gives a detailed explanation of the XBID components and describes the research question and the relevant assumptions. Section 3.4 reviews the CMT approach and shows its relation to the day-ahead and intraday market by mathematical formulations. Section 3.5 illustrates the CMT approach in a 6-node example. Several cases are discussed, where the capacities allocated in the day-ahead market vary, and where intraday trading starts from a feasible or infeasible day-ahead solution. Finally, Section 3.6 concludes the paper and future research is discussed.

3.2 Literature review

In the nodal pricing approach introduced by Schweppe et al. (1988), the nodal prices are the shadow prices of the power balance equations of the optimal economic power flow problem. The successful implementation of nodal pricing in North America, Australia and New Zealand has proven the efficiency of this powerful transmission pricing tool, without encountering significant technical problems. It has also been considered by the European Commission as one of the plausible approaches for integrating European electricity markets (Brunekreeft et al. (2005)).

In the 1990's however, there was a great debate about the efficiency of the nodal pricing approach. One of the most important objections, raised by Wu and Varaiya (1999), was the intervention of transmission system operators (TSOs) on economic or market decisions. In order to achieve a solution to the optimal economic dispatch problem, which on the one hand guarantees the security and reliability of the power system, and on the other hand promotes economic efficiency, strategic information about cost and demand functions (private information) of generators and consumers must be revealed to the TSO, who should just be responsible of technical support of the power system. Hence, the information structure and decision making authority are both centralized in the nodal pricing model.

Therefore, many attempts have been made to decouple these two distinct dimensions of the power system, by delegating economic efficiency responsibilities to power exchanges and technical support of the power system to the TSO. Nevertheless, they can never converge to a system optimal solution if a proper coordination is not established between them. Accordingly, the coordination models can be interpreted as various decomposition procedures for the optimal economic dispatch problem, wherein the dispatchers solve different subproblems, and subject to the subproblem structure, different information is exchanged back and forth with the TSO. Overall, these decomposition models can be classified into two groups:

1. Price-directed
2. Resource-directed

The method suggested by Chao and Peck (1996) is a price-directed scheme for explicit congestion pricing. In this method, scarce transmission resources are explicitly priced, and prices are communicated together with power transfer distribution factors (ptdfs), such that traders can acquire the necessary transmission capacity rights in order to do a transaction. In optimum, Chao-Peck prices are equivalent to optimal nodal prices.

Like the Chao-Peck price-directed method, the capacity charge approach suggested by Bjørndal et al. (2010) can be categorized as a price-driven decomposition of the optimal economic dispatch problem. By relaxing the line capacity constraints through Lagrangian relaxation, the constraints are implicitly managed by means of nodal capacity charges, which result in shifts in the nodal supply and demand curves. In other words, the social optimum solution is achieved by an iterative process between the TSO, who is announcing nodal capacity charges, and the power exchange, who is solving an unconstrained optimal dispatch problem by clearing the market with respect to the shifted supply and demand curves.

In the coordinated multilateral trade model presented by Wu and Varaiya (1999), only technical information related to the congested lines, signalling scarce resource availability (resource in this case means capacity of transmission lines) is announced by the TSO. Hence, the decision making authority related to economic and technical issues of the power system is broken up. Moreover, in the CMT model power exchanges can also be replaced by more decentralized entities, called brokers. After receiving supply and demand bids from interested generators and consumers, along with relevant signals from the TSO, the broker can find profitable multilateral trades, that move towards a feasible direction with respect to the announced technical limits. Thus, coordination is established through an iterative process, where power transfer distribution factors (ptdfs) of congested lines resulting from the last trades are announced by the TSO, and by utilizing the new information, brokers find new profitable trades. This process lasts until no further profitable trades can be found. Wu and Varaiya (1999) proved that the proposed CMT model will achieve the same economic efficiency and the same level of reliability as the nodal pricing model, meaning that social welfare is maximized with respect to the network constraints, provided that generators maximize profit and consumers maximize utility. Furthermore, instead of a broker, groups of generators and consumers with private terms and conditions of trade (without revealing their cost and benefit functions) can suggest balanced trades to the TSO. Consequently, in general no price can be extracted in the CMT model and it is not necessary that trades happen at the same time.

The CMT idea introduced in the 1990's, has been studied by Qin et al. (2017) for designing an innovative flexible market for smart grids. It is stated that the great flexibility of the CMT model, along with low communication and control burdens on the TSO, makes it an attractive approach for coordinating procedures in the distribution system. Moreover, by generalizing the CMT model from a deterministic settlement market setting (day-ahead) into a stochastic two-settlement market (day-ahead and real-time), they confirm that it is possible to achieve the same solution (maximizing expected social welfare) as a stochastic optimal dispatch model. Additionally, the dispatch and prices extracted from their model support competitive equilibrium under uncertainty (i.e. constitute an Arrow-Debreu equilibrium).

Since we suggest to utilize the CMT approach for a more efficient way of managing congestion in the intraday market, further details, related terminology and relevant mathematical models of the CMT model will be given in Section 3.4.4.

3.3 Problem description and assumptions

The sequence of day-ahead, intraday and balancing markets are cleared for each delivery hour of day d. In the European market design, the first two markets are cleared by power exchanges, only partly addressing the physical transmission network, while the last is typically organized by the TSOs, settling energy imbalances, while respecting day-ahead and intraday schedules, and considering the full transmission network. Therefore, the decoupling of the optimal economic dispatch problem by delegating the market efficiency responsibility to the power exchanges and security/reliability to the TSOs has been done before. Hence, the main idea of the CMT approach, which is the decoupling of decision making authorities, is already a reality in the European electricity market, but the information shared is different from the CMT model, although it is connected to transfer capacities. In the following, we will look more closely on the detailed design of the European intraday market.

In the XBID project, all orders of each power exchange will be shared in a shared order book (SOB) module, such that all market participants of other power exchanges located in other bidding zones can see them, provided that enough cross-border capacity, called Available Transfer Capacity (ATC), is available. The ATCs are provided by the relevant TSOs in the capacity management module (CMM). CMM provides two ATCs for each cross-border line, one for each direction. Orders submitted to different bidding zones can be matched provided there is enough capacity available. If two orders are matched, the SOB and CMM will be updated immediately. Trades are based on the first-come first-served principle, such that the highest bid price and the lowest ask price get served first. Whenever a matching happens, the SOB calculates the required quantity to be transferred between the source and destination zone. Then the CMM is responsible to find a routing plan which results in capacity allocations and thus updated ATCs.

The routing model applies a minimum cost flow model to select routes, i.e. routes with minimum cost that satisfy the flow constraints over cross-border lines. These cross-border lines, however, are edges of a graph which do not reflect accurately the physical transmission network. For instance, the model does not consider the externalities created by loop flows, which is a main characteristic of electricity networks. Consequently, like in the day-ahead market, it is very likely that the trades occurring in the intraday market lead to infeasible flows over physical transmission lines. Even if the flow-based market coupling model was used in the intraday market, it does not take into account the full nodal description of supply and demand, and will not achieve the same solution as the benchmark case of optimal nodal prices.

With the decision of the European Commission to integrate intraday markets with continuous trading, and with capacity and routing information provided by the TSOs, we consider the XBID market as an interesting opportunity for the CMT approach. The iterative nature of the CMT approach fits well with the intraday market, whether it is organized by continuous trading or by batch auctions. Moreover, the information needed from the TSOs in the CMT model is similar to the information already provided to the intraday market, although more details about the location of bids and ptdfs for detailed grid models are needed. With the CMT model applied to the intraday market, the responsibilities of power exchanges and TSOs are not mixed up, and by using ptdfs of detailed physical transmission lines in a market cleared prior to the balancing market, rather than the simplified network model of the day-ahead market, we should be able to reduce the costs of congestion management in the real-time balancing market.

In the following we develop the model, focusing on congestion management, and thus we apply some simplifying assumptions:

- In the day-ahead market, the power exchanges have access to zonal level information, which means that they know supply and demand functions for each zone, as well as aggregate transfer capacities (ATCs) between zones.
- In the suggested CMT intraday market, power exchanges receive supply and demand bids on nodal level, as well as technical (ptdf) information related to individual congested lines (this is contrary to the current intraday market design, where information is on zonal level).
- A single TSO (or a unit of cooperating TSOs) announces the ptdfs of congested lines in the whole region of governance, checks the feasibility of trades, and solves the curtailment problem.

3.4 Mathematical models

3.4.1 Notation

We adopt the same mathematical formulation as Bjorndal et al. (2016), where I denotes the set of market participants, either generators or consumers. For each $i \in I$, the quantity x_i will be either production (if $x_i > 0$)

or consumption (if $x_i < 0$). For the multistage trading process in Section 3.4.4, we will add the superscript k to denote the current stage, where $k = 0$ denotes the day-ahead market and $k \geqslant 1$ denotes some stage of the intraday market, and x_i^k is the production or consumption quantity corresponding to market participant i in stage k.

The cost function of generator i, where $x_i > 0$, can be of any type (quadratic, step-wise or piece-wise linear) and is denoted $c_i(x_i)$. For consumers, where $x_i < 0$, the benefit function is denoted $c_i(x_i)$. Thus, $c_i(x_i)$ can be interpreted as a cost function for all market participants. With multistage trading processes, as in Section 3.4.4, the cost or benefit functions could depend on the current stage k, but we will not consider such cases in this paper, since our focus is on congestion management only.

The production/consumption plans of the market participants are restricted by individual capacity constraints as well as by previous decisions. For the day-ahead market stage, the capacity constraints are represented as

$$x_i^0 \in C_i^0 \qquad\qquad i \in I, \tag{3.1}$$

where C_i^0 is the feasible set for market participant i in stage 0. In the intraday market, i.e., where $k \geqslant 1$, the feasible set C_i^k will also depend on previous decisions taken by participant i, i.e., the sequence $x_i^0, ..., x_i^{k-1}$ from previous stages. Therefore, a feasible solution in stage k must satisfy

$$x_i^k \in C_i^k(x_i^0, x_i^1, ..., x_i^{k-1}) \qquad\qquad i \in I. \tag{3.2}$$

For the benchmark case in Section 3.4.2, where the market is cleared in a single stage, we will omit the superscripts and just write C_i.

Each market participant i is located in a specific node $n \in N$, i.e., $i \in I^n$. Nodes of the network are connected by a set of physical transmission lines L. For each line $l \in L$, the flow is denoted f_l, and the corresponding thermal limit is denoted f_l^{max}. We will denote the starting and ending node of line l as $\nu_0(l) \in N$ and $\nu_1(l) \in N$, respectively. I.e., $f_l > 0$ indicates a power flow from $\nu_0(l)$ to $\nu_1(l)$, while $f_l < 0$ indicates flow in the opposite direction. Under a linear DC approximation (Schweppe et al. (1988)), flows can be related to nodal injections/withdrawals by constant power transfer distribution factors, where the factor $ptdf_{l,n}$ represents the flow over line $l \in L$ if 1 MW of power is injected at node $n \in N$ and withdrawn at the reference node.

Each market participant i is located in a pre-determined zone $z \in Z$, i.e., $i \in I^z$. For every pair of connected zones there is an interconnector $e \in E$ and a flow f_e. Similar to the notation for lines, we let $\omega_0(e) \in Z$ and $\omega_1(e) \in Z$ be the starting and ending zones of interconnector e, respectively. Hence, $f_e > 0$ means that the commercial flow goes from $\omega_0(e)$ to $\omega_1(e)$, whereas $f_e < 0$ means that the flow goes in the opposite direction. We will assume that the zonal day-ahead market is cleared with lower (ATC_e^{min}) and upper (ATC_e^{max}) bounds on the commercial flow over interconnection $e \in E$.[1]

3.4.2 Nodal benchmark model

Model (3.3) describes a day-ahead market with nodal pricing. The objective (3.3a) minimizes total net cost, which is equivalent to maximizing total welfare. For each market participant $i \in I$, (3.3b) represents the respective

[1] Unlike transmission line constraints, where the thermal capacity limit f_l^{max} determines both the upper and lower bound for f_l, we do not necessarily have $ATC_e^{min} = -ATC_e^{max}$, since system operators, when setting the ATCs, will try to ensure feasibility for the entire system.

production/consumption constraints. For every node $n \in N$ we define τ_n as injection from the node to the grid, and (3.3c) links net injection to the sum of production and consumption in the node. The flow over each line $l \in L$ is linked to the nodal net injections in (3.3d), and the thermal flow limits are enforced by (3.3e).

$$\underset{x,f,\tau}{\text{Minimize}} \quad \sum_{i \in I} c_i(x_i) \tag{3.3a}$$

$$\text{subject to} \quad x_i \in C_i \qquad i \in I \tag{3.3b}$$

$$\tau_n = \sum_{i \in I^n} x_i \qquad (\lambda_n) \qquad n \in N \tag{3.3c}$$

$$f_l = \sum_{n \in N} ptdf_{l,n} \cdot \tau_n \qquad l \in L \tag{3.3d}$$

$$-f_l^{max} \leqslant f_l \leqslant f_l^{max} \qquad l \in L \tag{3.3e}$$

Since we do not consider uncertainty in this paper, and since (3.3) includes a complete description of the network constraints, as given by the linear DC approximation, it will give us the first-best solution, i.e., a natural benchmark for our analyses, including optimal nodal prices, λ_n.

3.4.3 Zonal day-ahead market

The current European electricity market setup is a sequential system consisting of the day-ahead, intraday, and balancing markets. The markets are cleared with deterministic models, meaning that uncertainty about intraday and real-time events are not taken into consideration in the day-ahead stage, at least not explicitly. The equations in (3.4) describes our mathematical formulation of the day-ahead market clearing.

$$\underset{x,f,\tau}{\text{Minimize}} \quad \sum_{i \in I} c_i(x_i^0) \tag{3.4a}$$

$$\text{subject to} \quad x_i^0 \in C_i^0 \qquad i \in I \tag{3.4b}$$

$$\tau_z = \sum_{i \in I^z} x_i^0 \qquad (\lambda_z) \qquad z \in Z \tag{3.4c}$$

$$\tau_z = \sum_{e:\omega_0(e)=z} f_e - \sum_{e:\omega_1(e)=z} f_e, \qquad z \in Z \tag{3.4d}$$

$$ATC_e^{min} \leqslant f_e \leqslant ATC_e^{max} \qquad e \in E \tag{3.4e}$$

As mentioned in Section 3.4.1, x_i^0 is the vector of production/consumption at the day-ahead market. The objective (3.4a) is the same as in the nodal benchmark model (3.3). The constraint (3.4b) reflects any kind of constraints that market participant i is confronted with at the day-ahead market. The constraint (3.4c) defines the net injection τ_z from zone z to the grid, and the shadow price, λ_z, represents the day-ahead clearing price of the zone. Constraint (3.4d) links the zonal net injection to the flow over the relevant interconnectors. Finally, constraint (3.4e) enforces the inter-zonal trading capacities.

3.4.4 Coordinated multilateral trading concepts

The novel idea introduced by Wu and Varaiya (1999) and then developed by Qin et al. (2017), is that a free-market style of meet-and-trade, instead of a centralized infrastructure with high level of coordination, is able to provide an opportunity for all generators and consumers to seek profit on their own, implying that they can conduct the economic function themselves, deciding about price, trading terms and conditions, as well as trading quantity. Hence, the direct effect of this mechanism is that price information is private.

However, the idea of meet-and-trade without any coordination with the TSO could result in flows that violate the transmission capacity constraints. Consequently, Wu and Varaiya suggested an idea where the TSO and free traders coordinate with as little information sharing as possible, such that a feasible solution is attained at every stage. Therefore, they even neglected the power exchange role and just let market participants coordinate with the TSO, either directly or with the help of a broker. Hence, trades between two or more market players is the main element of such a market design.

Even if the definition of multilateral, feasible, feasible direction and profitable trades, as well as other related terminology, have been fully explained in Wu and Varaiya (1999) and expanded to models with uncertainty by Qin et al. (2017), we will give a short review, customized to our purposes. The building blocks of continuous trading, as in current intraday markets, are bilateral trades. However, as Wu and Varaiya (1999) proved, it is not possible to relieve congestion in a network by bilateral trades only. Hence, multilateral trades may be necessary to ensure convergence to the optimal nodal solution.

Definition 1. Multilateral trade. A trade involving more than one party, such that, in a lossless system, the sum of the traded quantities is equal to zero. Mathematically, a multilateral trade involving the participants $I' \subset I$, is a vector $\Delta x = (\Delta x_i)$, where Δx_i is the traded quantity for participant $i \in I$, such that $\sum_{i \in I'} \Delta x_i = 0$ and for $i \notin I'$, $\Delta x_i = 0$.

The current plan x is the sum of all previous trades. The TSO can calculate the resulting network flow as

$$f_l = \sum_{n \in N} ptdf_{l,n} \cdot \sum_{i \in I^n} x_i \qquad l \in L, \tag{3.5}$$

and the flow will be feasible if

$$-f_l^{max} \leqslant f_l \leqslant f_l^{max} \qquad l \in L. \tag{3.6}$$

Given that x is the current plan, and that it is feasible, i.e., satisfies (3.5) and (3.6), a new trade Δx may cause one or more of the inequalities in (3.6) to be violated. If that is the case, then the TSO might have to curtail the trade.

Definition 2. Uniform curtailment. In order to make sure that the new plan is feasible, the TSO will only accept a portion $\gamma \in [0, 1]$ of the trade Δx, such that $x + \gamma\Delta x$ is feasible. $\gamma = 1$ means that the whole trade Δx is accepted without curtailment.

A feasible direction trade is a trade that does not increase the net power flow over lines that are already congested.

Definition 3. Feasible direction trade. Let L_c denote the set of congested lines. If x is feasible, and if the resulting flow f satisfies

$$f_l = f_l^{max} \qquad l \in L_c, \tag{3.7}$$

$$f_l < f_l^{max} \qquad l \notin L_c, \tag{3.8}$$

then Δx is a feasible direction trade at x if

$$\sum_{n \in N} ptdf_{l,n} \cdot \sum_{i \in I^n} \Delta x_i \leqslant 0 \qquad l \in L_c. \tag{3.9}$$

Definition 4. Profitable multilateral trade. Assume that x is feasible. A trade Δx is profitable at x if it reduces the total cost (increases social welfare).

Definition 5. Broker. The third party entity that arranges the trades.

As we mentioned before, after curtailing the infeasible flows resulting from the broker's solution, the TSO announces the congested lines (lines at maximum flow) and their related ptdfs. Hence, the broker receives new signals for going in the right direction. The broker's decision making problem is very similar to the economic dispatch model. However, instead of modeling the full transmission network, a broker tries to move toward feasibility with regards to the signals obtained from the TSO. In general, a broker can modify the previously allocated schedules by finding profitable deviations from the current schedule. These deviations could be positive or negative. Positive deviations, i.e. $\Delta x > 0$, may be due to:

- Increase in power production from flexible generators, meaning that the generators want to sell an extra amount of energy in the current stage of the intraday market.
- Decrease in power consumption from flexible loads, i.e. consumers resell power that is bought previously.
- Extra production from intermittent renewable power generators, for instance because updated forecasts show an increase in available power, which can be sold in the current stage of the intraday market.

Likewise, negative deviations, i.e. $\Delta x < 0$, can be due to:

- Decrease in power production from flexible generators, meaning that the generators will buy back power.
- Increase in power consumption.
- Production reductions from intermittent renewable generators, for instance because of new forecasts showing less availability of power.

Considering the broker problem, it is obvious that if more parties are involved, the higher the chance is to find a more profitable solution. In this respect, the best case is if all generators and consumers are involved in the broker's problem, which then will be identical to a fully coordinated auction operated by the power exchange. The meet-and-trade approach suggested by Wu and Varaiya (1999) and Qin et al. (2017) demonstrates the possibility of reaching an efficient market outcome in a decentralized setting, under strong assumptions of zero search cost and perfect information. They don't imply that a decentralized market is superior to a centralized in practice, as there may be significant search costs for finding the right trading partners, unless there is some information platform that collects participants' cost/benefit information and shares it with suitable parties. A good market structure could be some middle ground between a fully centralized market and a fully decentralized one, as centralization requires significant communication cost while decentralization leads to higher search cost. Another benefit of the decentralized approach is that the centralized solution can be contested.

3.4.5 Intraday market with coordinated multilateral trading

The intraday market serves several purposes, as reviewed by Rahimi et al. (2018). One purpose is to handle unexpected events, like unplanned power plant outages, forecast errors from intermittent renewable energy sources, load forecast errors, etc. Also, as mentioned in Section 3.4.3, since the day-ahead market (3.4) is modeled as a partly network-constrained auction, most probably the day-ahead solution does not satisfy the physical network constraints (3.5) and (3.6), and the intraday market may help relieving the remaining congestion. In this paper, our focus is on congestion management, and we will not consider deviations due to uncertainty or changes in forecasts in the illustrations that follow.

With additional detailed locational information about bid and ask offers, as well as the technical information about ptdfs of congested lines provided to the power exchanges, the limit order book of the European power exchanges may work exactly as a facilitating information platform for traders. Market participants can find trading partners to a feasible direction trade without paying the high search costs of the meet-and-trade approach, and without necessarily having to reveal private information such as cost functions to the power exchange. Thus, the limit order book may function as an infrastructure for allowing continuous decentralized multilateral trades by brokers. It may however also serve as an infrastructure for running batch auctions, such that for every batch auction, a subset of participants take part and are cleared. The clearing result can be interpreted as a multilateral trade among this subset of participants. As an extreme, the power exchange itself can take on the role as broker.

If we were to model decentralized trades or batch auctions, we would have to model some kind of random arrival of buyers and sellers. If we were to model forecasting errors of renewable generators, or how information is revealed over time, this would be a natural approach. Since we want to focus on the congestion management aspects, and assume that supply and demand functions are fixed as in day-ahead, we simplify the exposition and assume that the exchange takes on the broker role, running auctions with all participants involved. Thus, the power exchange and TSO problems are attained by decomposing the optimal economic dispatch problem such that the power exchange problem is considered to be the master problem, while the TSO problem is the subproblem, and the feasible direction trade constraints are linking cuts.

In the following, we will use the CMT concepts, introduced in the previous section, to construct two alternative intraday market procedures, as shown in Figure 3.1. Both procedures start from the day-ahead solution, which may be infeasible. The main difference between procedures A and B is how they treat the initial day-ahead solution:

A. In this approach we follow exactly the same procedure as the CMT approach, but we curtail the day-ahead solution to get an initial feasible trade before starting the intraday market. The advantage of this approach is that we will reach the optimal nodal solution at the end of the intraday market iterations, as proved by Wu and Varaiya (1999). It is however, an open question whether and how the day-ahead market participants, that are affected by the curtailment, should be compensated.
B. Start the intraday market with a day-ahead solution that may be infeasible. The difference with respect to procedure A is, as we will show in Section 3.5, that we do not necessarily reach the optimal nodal solution, but we could reach a solution that is more profitable and more feasible than the starting solution.

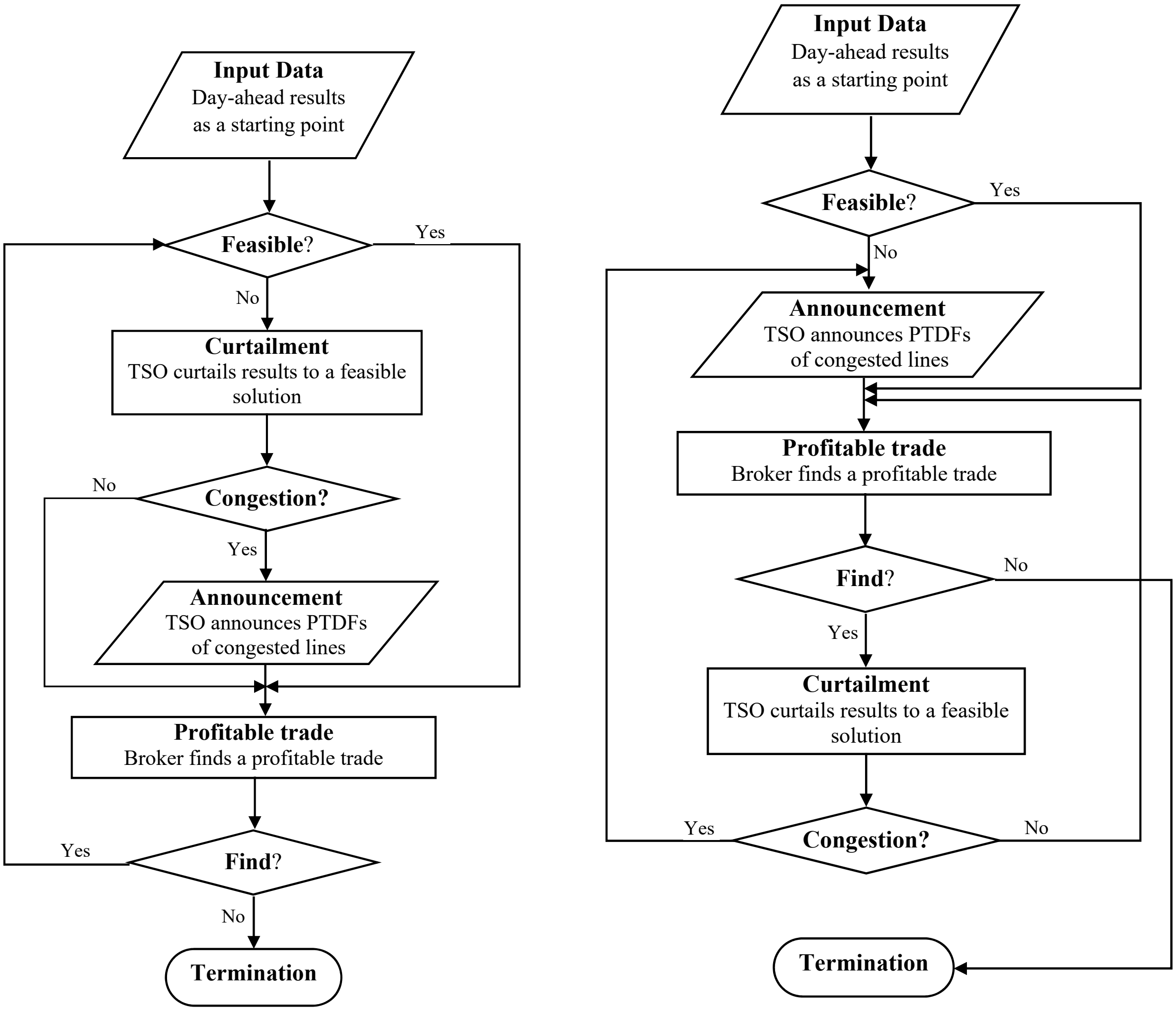

Figure 3.1. CMT process description under alternative A (left) and B (right).

We will refer to the plan in iteration k as x^k, where $k = 0$ represents the day-ahead solution. The initial curtailment in Procedure A is done by the TSO, who will solve (3.10) in order to maximize the curtailment factor γ, i.e., accept as much as possible of the initial solution x^0, such that the curtailed solution γx^0 satisfies the network constraints (3.10b)-(3.10d).

$$\text{Maximize}_{\gamma,f,\tau} \quad \gamma \tag{3.10a}$$

$$\text{subject to:} \quad \tau_n = \sum_{i \in n} \gamma x_i^0, \qquad n \in N \tag{3.10b}$$

$$f_l = \sum_{n \in N} ptdf_{l,n} \cdot \tau_n \qquad l \in L \tag{3.10c}$$

$$-f_l^{max} \leqslant f_l \leqslant f_l^{max} \qquad l \in L \tag{3.10d}$$

$$0 \leqslant \gamma \leqslant 1 \tag{3.10e}$$

After the initial curtailment in Procedure A, we make the assignment $x^1 \leftarrow \gamma x^0$. For Procedure B, where no initial curtailment is done, we assign $x^1 \leftarrow x^0$.

In every iteration k, the TSO will announce the ptdfs of the congested lines, i.e., the lines belonging to the set

$$L_c^k = \{l \in L : |f_l| = f_l^{max}\}. \tag{3.11}$$

Based on the definition from Wu and Varaiya (1999), a broker can facilitate the trades between generators and consumers by finding profitable trades in the feasible direction via the optimization problem (3.12), where $I^k \subset I$ is the set of generators and consumers participating in the trade.

$$\begin{aligned}
&\text{Maximize}_{\Delta x^k} && \sum_{i \in I^k} c_i(x_i^k) - c_i(x_i^k + \Delta x_i^k) && && (3.12a)\\
&\text{subject to:} && \sum_{i \in I^k} \Delta x_i^k = 0 && && (3.12b)\\
& && \sum_{n \in N} ptdf_{l,n} \cdot \sum_{i \in I^n \cap I^k} \Delta x_i^k \leqslant 0 && l \in L_c^k && (3.12c)\\
& && x_i^k + \Delta x_i^k \in C_i^k \left(x_i^0, ..., x_i^{k-1}\right) && i \in I && (3.12d)
\end{aligned}$$

The objective (3.12a) of the broker problem is to find Δx^k such that the cost reduction by moving from x^k to $x^k + \Delta x^k$ is maximized, subject to the power balance constraint (3.12b) and the feasible direction trade constraint (3.12c) for congested lines. A profitable trade, according to Definition 1, is an optimal solution where the value of (3.12a) is positive.

Profitable trades found by the broker may lead to infeasible flows, so the TSO may need to curtail them by solving (3.13), similar to the initial curtailment problem (3.10) in Procedure A.

$$\begin{aligned}
&\text{Maximize}_{\gamma,f,\tau} && \gamma && && (3.13a)\\
&\text{subject to:} && \tau_n = \sum_{i \in n} x_i^k + \gamma \Delta x_i^k, && n \in N && (3.13b)\\
& && f_l = \sum_{n \in N} ptdf_{l,n} \cdot \tau_n && l \in L && (3.13c)\\
& && - f_l^{max} \leqslant f_l \leqslant f_l^{max} && l \in L && (3.13d)\\
& && 0 \leqslant \gamma \leqslant 1 && && (3.13e)
\end{aligned}$$

After curtailment, we initialize the next iteration with $x^{k+1} \leftarrow x^k + \gamma \Delta x^k$, and repeat the process.

3.5 Numerical example and results

In this section, a small deterministic 6-bus system is used to clarify how our suggested CMT-based intraday market can be implemented. With a deterministic example, it is easier to explore how the trading process is managed by the CMT model. The 6-bus example is depicted in Figure 3.2. The system consists of 2 zones $z \in \{Z_1, Z_2\}$ (which can be interpreted as 2 countries), 6 nodes $n \in \{n_1, ..., n_6\}$, 3 conventional generators $g \in \{G_1, G_2, G_3\}$ placed at nodes 1, 2 and 5, respectively. Moreover, there are 3 elastic loads, $d \in \{D_1, D_2, D_3\}$, located at nodes 3, 4, and

6, and finally 8 lines $l \in \{L_1, ..., L_8\}$. The capacity of the lines is also shown in Figure 3.2. The susceptance of all lines and the resulting ptdf matrix is illustrated in Table 3.1.

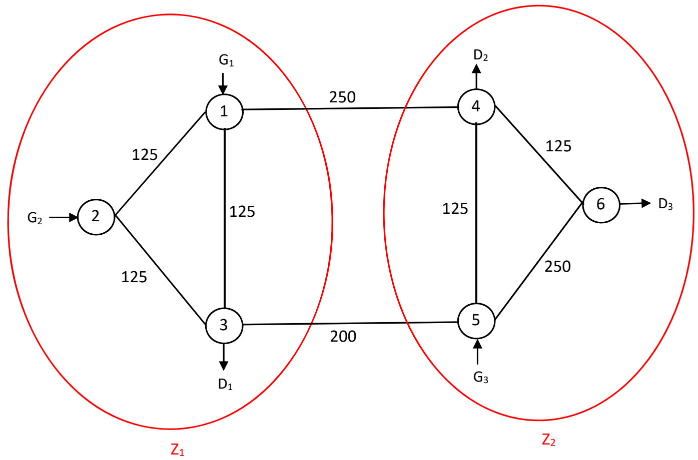

Figure 3.2. 6-bus example

Table 3.1. Line parameters.

Lines	Susceptance	PTDF					
		n_1	n_2	n_3	n_4	n_5	n_6
1-2	1	0.088	-0.530	-0.105	0.030	-0.020	0
1-3	1.5	0.279	-0.011	-0.332	0.094	-0.064	0
1-4	1.6	0.634	0.540	0.437	-0.124	0.084	0
2-3	0.9	0.088	0.470	-0.105	0.030	-0.020	0
3-5	1.1	0.366	0.460	0.563	0.124	-0.084	0
4-5	1.3	0.160	0.095	0.023	0.329	-0.223	0
4-6	0.95	0.474	0.446	0.414	0.547	0.307	0
5-6	1.4	0.526	0.554	0.586	0.453	0.693	0

The related market participants' data is as follows:

- G_1 is a nuclear power plant with capacity of 450 MW, and a constant marginal cost of 12 €$/MWh$.
- G_2 is a gas power plant with 350 MW capacity and a constant marginal cost of 20 €$/MWh$.
- G_3 is a coal power plant with hard coal fuel, the capacity of this plant is 400 MW and its marginal cost of production equals 17 €$/MWh$.
- D_1 is a load with medium willingness to pay of 23 €$/MWh$ and maximum consumption of 450 MW.
- D_2 is a load with low willingness to pay of 21 €$/MWh$ and consumption capacity of 400 MW.
- D_3 is a load with high willingness to pay of 30 €$/MWh$ and maximum consumption of 350 MW.

There is one interconnector e between zones z_1 and z_2. Based on the ATC of this interconnector and the different approaches mentioned in Section 3.4.5, several cases will be discussed in the subsequent sections.

3.5.1 Benchmark: Optimal nodal solution

In Figure 3.3 we display the optimal economic dispatch, with optimal generation, consumption, line flows, and nodal prices. This constitutes the benchmark solution. Line capacities are given by numbers in black, while the resulting line flows are given by numbers in red. We have marked line flows that are at (and later also above) their capacity limit by putting a green oval around the numbers.

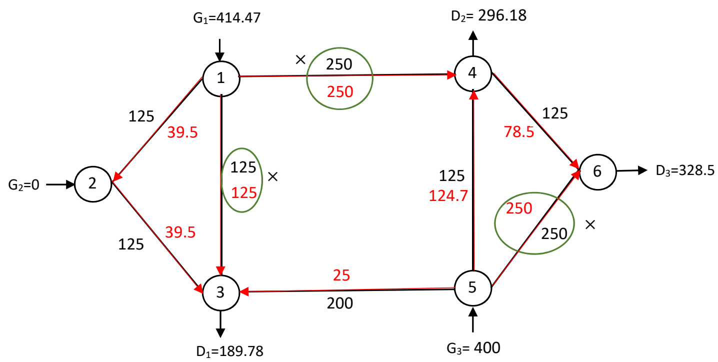

Figure 3.3. Optimal nodal solution with social surplus = 8666.5.

3.5.2 Starting point: Day-ahead solutions

We will test Methods A and B with two different starting points, depending on how the ATC capacities are set by the TSO.

If the TSO sets $ATC = \infty$ we get the solution shown in Figure 3.4. The physical flows resulting from the day-ahead schedule are given by numbers in red, and we see that the flow capacities of several lines are violated.

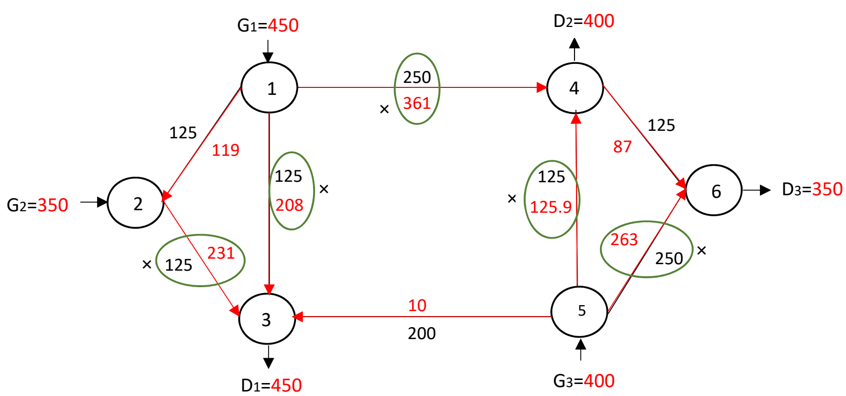

Figure 3.4. Day-ahead clearing result with $ATC = \infty$. Social surplus = 10050.

On the other hand, if the TSO sets $ATC = 0$ we get the solution shown in Figure 3.5. Again, the solution is infeasible, since the flow over line 1-3 is larger than its capacity.

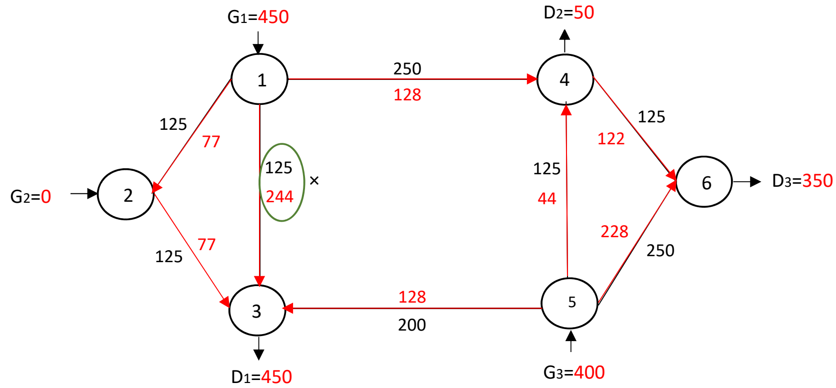

Figure 3.5. Day-ahead clearing result with $ATC = 0$. Social surplus = 9700.

3.5.3 Method A: Curtail day-ahead before intraday starts

3.5.3.1 $ATC = \infty$

According to Method A, the DA schedule shown in Figure 3.4 is curtailed, based on (3.10), resulting in the solution in Figure 3.6.

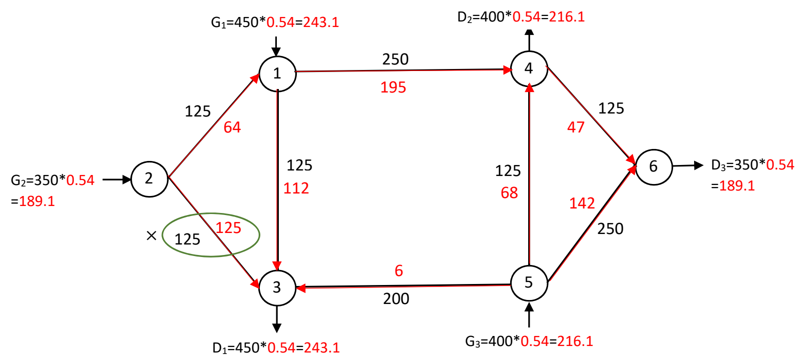

Figure 3.6. Curtailed starting solution ($\gamma = 0.54$).

Now, profitable trades are found with (3.12), resulting in the revised schedule in Figure 3.7.

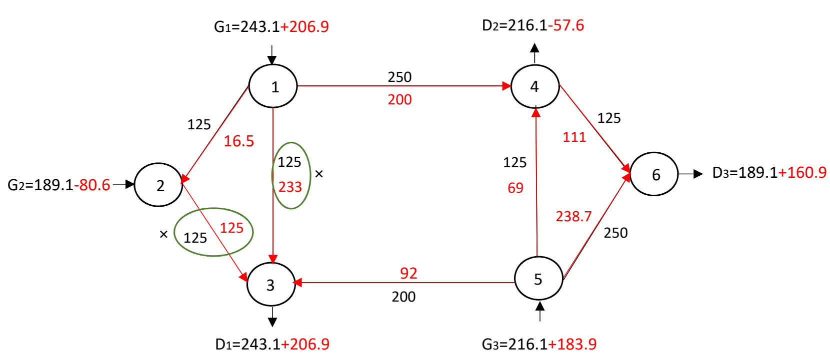

Figure 3.7. Iteration 1 - profitable trade. Social surplus = 4380.

In order to achieve feasibility, the TSO curtails the schedule by solving (3.13), and we get the schedule in Figure 3.8.

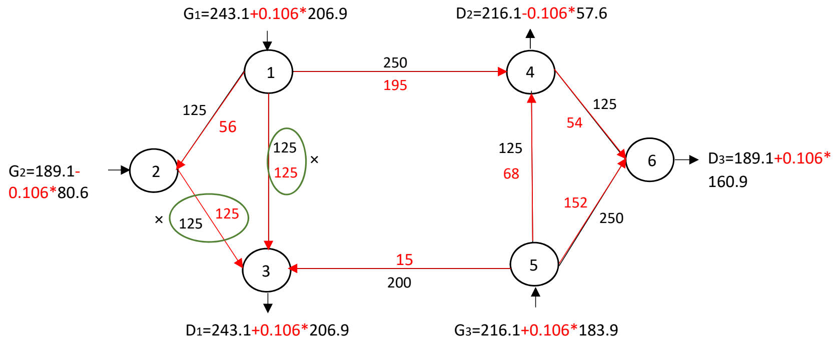

Figure 3.8. Iteration 1 - TSO curtailment ($\gamma = 0.106$).

This process continues until, after 4 iterations, no further profitable trades can be found, and we end up with the schedule in Figure 3.14. We note that the final solution is also equal to the optimal nodal solution in Figure 3.3.

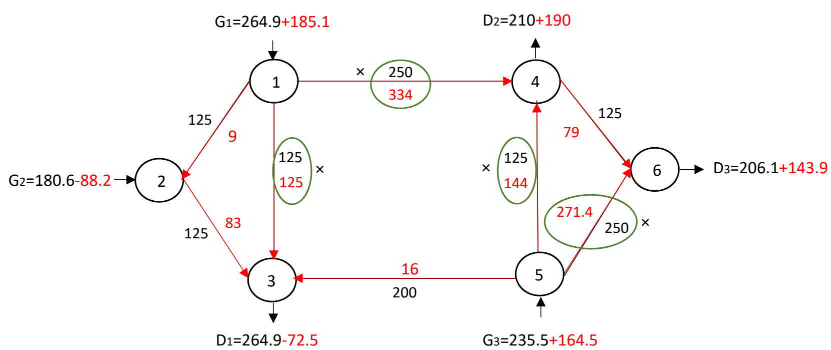

Figure 3.9. Iteration 2 - profitable trade. Social surplus = 3386.

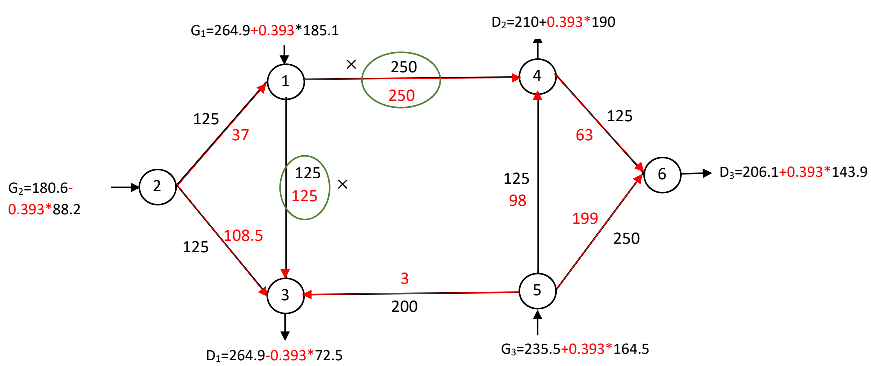

Figure 3.10. Iteration 2 - TSO curtailment ($\gamma = 0.393$).

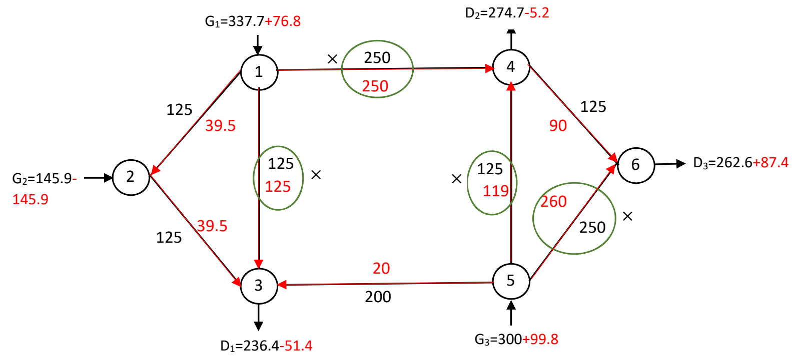

Figure 3.11. Iteration 3 - profitable trade. Social surplus = 1628.

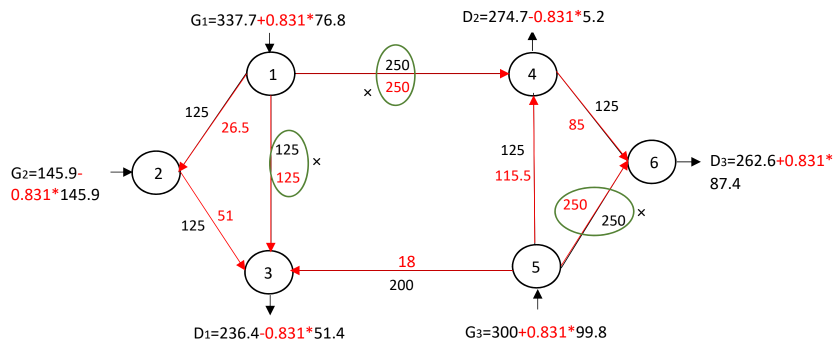

Figure 3.12. Iteration 3 - TSO curtailment ($\gamma = 0.831$).

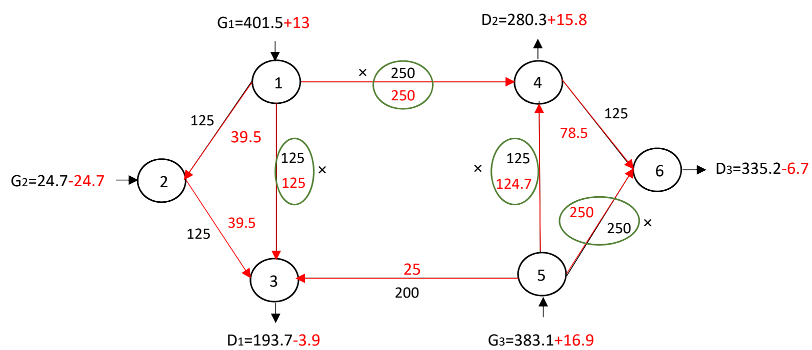

Figure 3.13. Iteration 4 - profitable trade. Social surplus = 92.

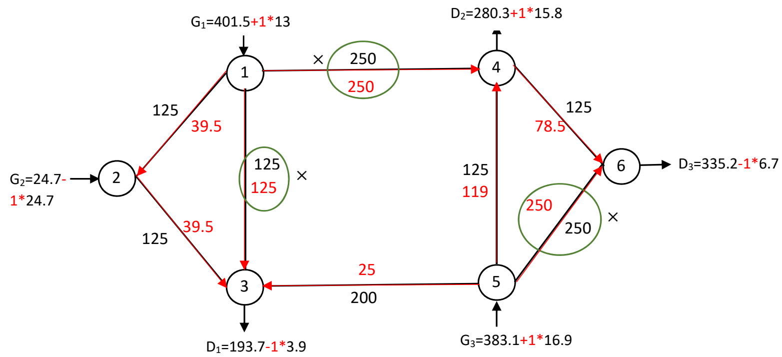

Figure 3.14. Iteration 4 - TSO curtailment not necessary ($\gamma = 1$).

3.5.3.2 $ATC = 0$

We apply (3.10) to the day-ahead solution shown in Figure 3.5, resulting in the curtailed starting point in Figure 3.15. Figures 3.16-3.21 show the results of 3 iterations, after which no more profitable trades can be found. Again, the final solution in Figure 3.21 is equal to the optimal nodal solution in Figure 3.3.

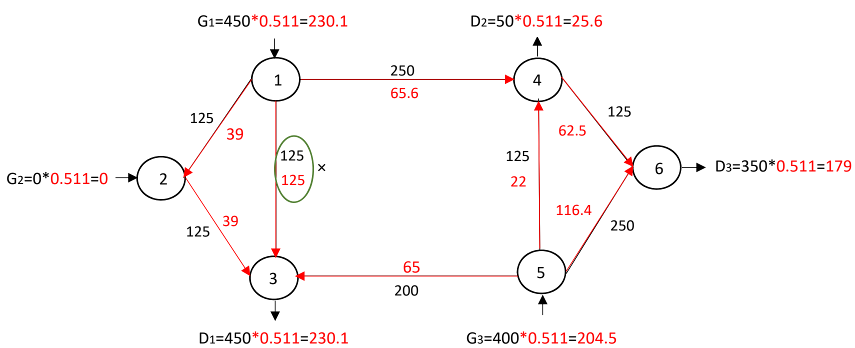

Figure 3.15. Curtailed starting solution ($\gamma = 0.511$).

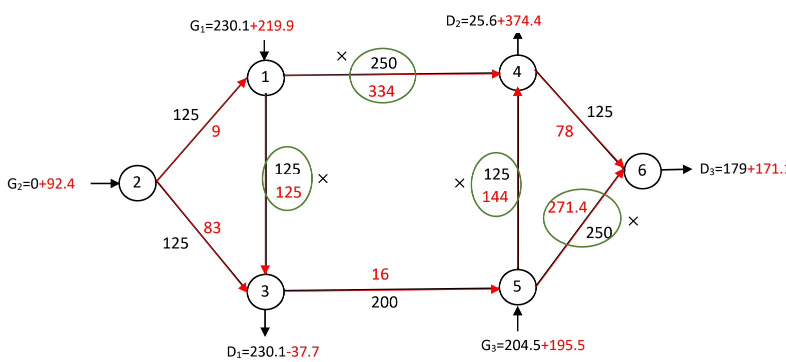

Figure 3.16. Iteration 1 - profitable trade. Social surplus = 4318.

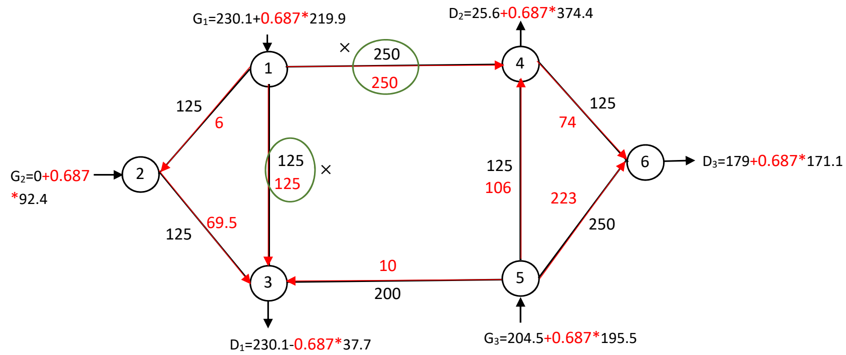

Figure 3.17. Iteration 1 - TSO curtailment ($\gamma = 0.687$).

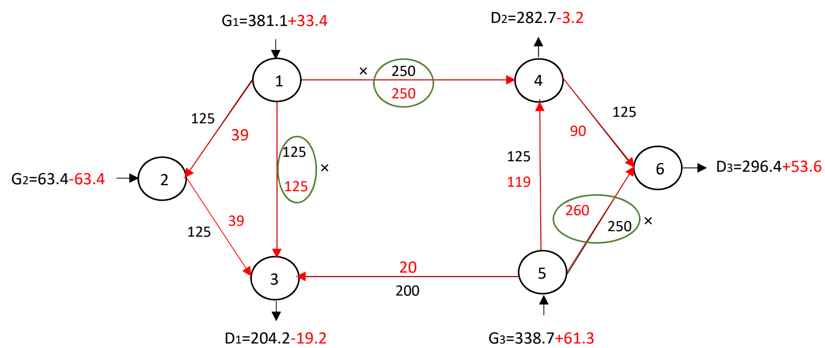

Figure 3.18. Iteration 2 - profitable trade. Social surplus = 926.

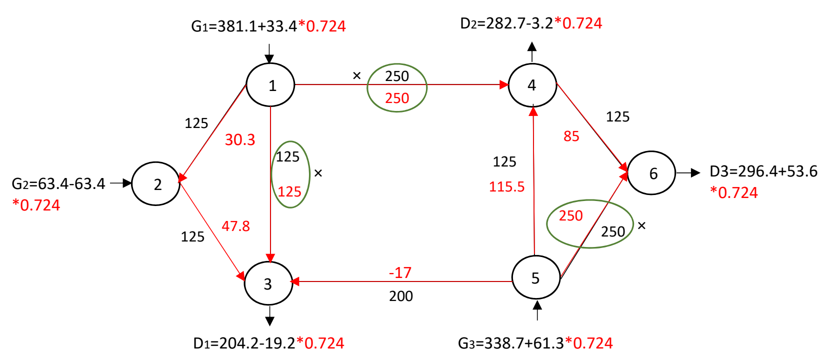

Figure 3.19. Iteration 2 - TSO curtailment ($\gamma = 0.724$).

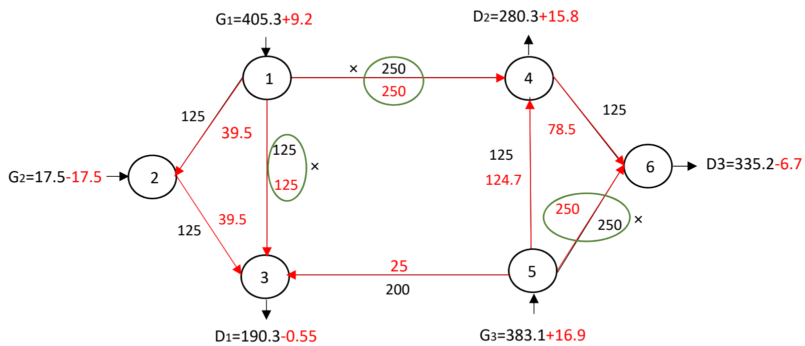

Figure 3.20. Iteration 3 - profitable trade. Social surplus = 72.

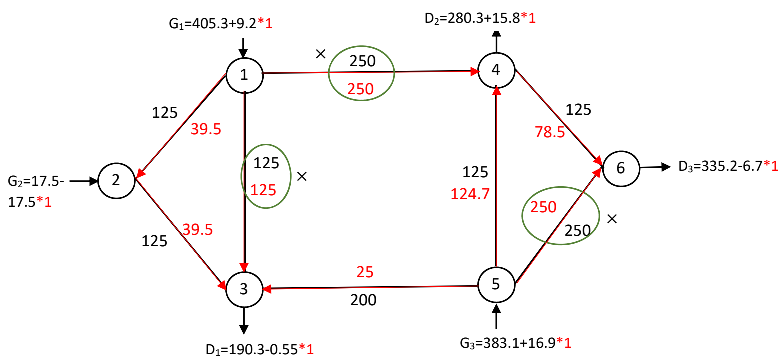

Figure 3.21. Iteration 3 - TSO curtailment not necessary ($\gamma = 1$).

3.5.4 Method B: Start intraday from (possibly infeasible) day-ahead solution

3.5.4.1 $ATC = \infty$

We start Method B from the day-ahead solution shown in Figure 3.4. When we apply (3.12) to this solution, we cannot find any profitable trades. Hence, for this example, Method B is not able to detect any trades that can relieve the congestion.

3.5.4.2 $ATC = 0$

Starting with the uncurtailed day-ahead solution shown in Figure 3.5, we apply (3.12), resulting in the solution shown in Figure 3.22. Curtailment by (3.13) then gives the solution in Figure 3.23.

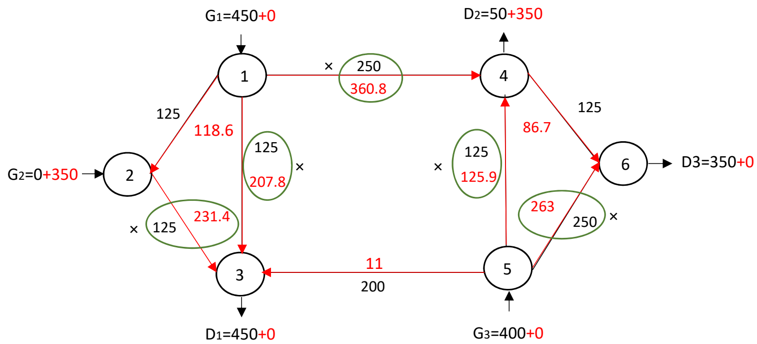

Figure 3.22. Iteration 1 - profitable trade. Social surplus = 350.

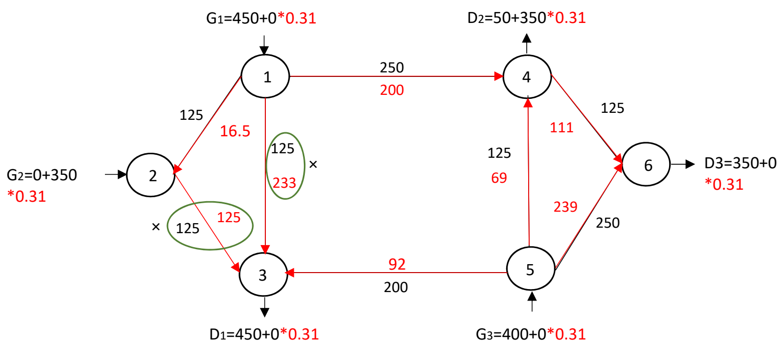

Figure 3.23. Iteration 1 - TSO curtailment ($\gamma = 0.31$).

In this case, no further profitable trades can be found, so the procedure stops after just one iteration. We notice that the final solution is not feasible, since the capacity of line 1-3 is still violated. However, it is closer to being feasible than it was in the day-ahead solution, since the flow over line 1-3 has been reduced, and no other constraints are violated. Interestingly, it turns out that the final solution in Figure 3.23 is identical to the optimal economic dispatch that we obtain if we relax the capacity constraint of the violated line 1-3, and set it equal to the flow resulting from the day-ahead solution. This solution is shown in Figure 3.24.

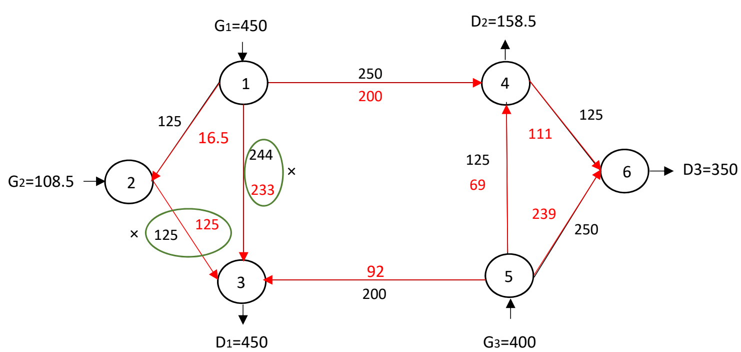

Figure 3.24. Optimal economic dispatch with relaxed capacity constraint on line 1-3.

3.5.5 Summary of example

If the day-ahead solution can be curtailed, as with Method A, we can reach the optimal nodal solution. It does not matter which ATC capacity the day-ahead solution is based on, except that the convergence time will be affected. In the example, we have used the uniform curtailment method of the CMT approach. However, in practice, other methods to obtain a feasible starting solution before the intraday market opens could also be applied, such as redispatch or counter trading.

If the day-ahead solution cannot be curtailed, as with Method B, the CMT-based intraday market will not worsen any physically overloaded links, as long as the load factors/ptdfs of these constraints are communicated to the market place. On the contrary, The CMT approach can help to get closer to a feasible solution, if profitable trades can be found in a feasible direction. The final solution will depend on the ATC capacities used in the day-ahead market, and we can have cases where no profitable trades can be found. The final solution will in general not be equal to the optimal nodal solution, but corresponds to the optimal solution of a relaxed optimal economic dispatch problem, where the capacity of links that are violated in the day-ahead solution is set equal to the day-ahead flows.

3.6 Conclusions

Electricity markets across the world differ substantially when it comes to dealing with transmission constraints and the complexities created by the loop flow characteristics of electricity. This is reflected in the nodal/zonal debate, where for instance the North American and European power markets have chosen different solutions. The coordinated multilateral trade (CMT) model is equivalent to the nodal pricing model when it comes to efficiency, but differs when it comes to the coordination mechanism (technical information about power transfer distribution factors of congested lines) and information needs and responsibilities for market operators and market participants. With the present developments in the European intraday markets, with a joint limit order book, and information about transfer capacities provided by the TSOs, we argue that the CMT model could be used in the European intraday market, in order to incorporate more detailed information about location of bids and their influence on congested lines in the system. The benefit would be that intraday trades could improve, and at least not worsen, capacity constraints in the physical electricity networks. The CMT model can be used in a decentralized setting, with brokers organizing trades continuously, but it can also be used if frequent batch auctions were to be introduced in the market.

In this paper, we have outlined the CMT model in the setting of the European intraday market, and we have discussed the information needs if the CMT model is to be an efficient procedure for managing transmission constraints in the integrated European intraday markets. The European power exchanges run the day-ahead markets based on the Euphemia algorithm, which needs zonal level data, while the requirements of the CMT approach is access to nodal level data. This means that if the power exchanges have access to nodal level supply and demand functions for the intraday market, then the coordination between power exchanges and TSOs can be done just by transferring technical information. We have illustrated the iterative CMT procedure on a small 6-node example, illustrating that the number of iterations and the final result depends on the capacities given to the day-ahead market (assuming the ATC model) and whether the starting point of the intraday market is the solution to the day-ahead market or a curtailed (and therefore feasible) solution. Even if we start the intraday market from an infeasible day-ahead solution, the intraday trading can improve the constraints by finding profitable trades that don't aggravate overloads.

Since we have focused on the congestion management aspects, we have assumed that supply and demand functions are the same in day-ahead as in the different intraday market stages. Implicitly this means that the only purpose of the intraday market is to reduce imbalance costs due to the network simplifications in the day-ahead market. Even in this simplified setting, further research is required to understand whether the number of iterations in the CMT based intraday market is tractable for realistic networks, and how it depends on settings in the day-ahead market. Another avenue for further research is to assess the CMT model in relation to other important purposes of the intraday markets, like handling of unexpected events, forecasting errors in intermittent generation, etc.

Chapter 4

Optimal Timing of Intraday Electricity Auctions: Striking a Balance Between Flexibility Cost and wind Uncertainty

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Abstract

With the Europe 2020 strategy, that targeted 20% of gross final energy consumption from renewable sources by 2020, the security of power systems has been confronted with new challenges due to the stochastic nature of renewable generation. Consequently, the EU Commission has set the electricity market design reforms high on the agenda. Because of this, it has been decided to complement the already established power markets with pan-European intraday auctions. On the one hand, these auctions allow to price cross-zonal capacity, and on the other hand, by providing new trading opportunities closer to the delivery hour, the risk for the intermittent generators to be imbalanced in the real-time diminishes. The optimal timing of these auctions is affected by two contradictory factors; by getting closer to the delivery hour there will be lower uncertainty due to the more accurate forecasts, and higher flexibility costs of the system due to the activation of more expensive flexibility providers. In this paper, standard deviation (STD) is used as a measure of uncertainty. By experimenting with several scenario trees where the standard deviation (STD) is declining from day-ahead to real-time, we find that in a sequential market setting, STD reduction itself is not enough to say that the latest intraday option is the best (by fixing the other variables). STD is mainly reflected in re-adjustment quantities and therefore, the multiplicative effect of flexibility cost and re-adjustment quantities determine the optimal intraday place not the trade-off between flexibility cost and STD reduction. Furthermore, an optimal intraday auction placement vigorously depends on the technological combination in the considered market. For instance, in hydro-dominated systems adding an intraday auction does not have any salient effect while in systems with large share of thermal plants with high flexibility costs, adding an intraday auction could be hugely cost-effective.

Keywords: Renewable integration, Sequential markets, Intraday auctions, Multi-stage scenario tree generation, Conditional expectations, clustering (bucketing) approach

4.1 Introduction

The decision of the European Commission to integrate European intraday markets by a common continuous trading approach, has unveiled new challenges regarding the pricing of cross-zonal capacity. The guideline on capacity allocation and congestion management (CACM) requires methods for pricing the capacity that market participants can use on cross-border lines (Commission Regulation (EU), (2015)), while continuous trading is not in line with this guideline (NVE THEMA Consulting Group (2019)). In continuous trading, available capacity is allocated based on a first-come-first-serve principle, and if only parts of the cross-border capacity is assigned to the first cleared trade, the capacity is not scarce. If, after subsequent trades, the capacity becomes scarce, it is not possible for capacity owners to place a value on this scarcity, because it has already been assigned at no cost. Hence, allocating capacity to the continuous trading intraday market may not only result in revenue loss for capacity owners, but may also provide insufficient signals and incentives for efficient assignment and development of cross-zonal capacity. Therefore, in spite of the fact that CACM requires pricing of cross-zonal capacity to be part of the market design, thus far the continuous intraday market does not include this feature.

Consequently, the Agency for the Cooperation of Energy Regulators (ACER) has decided to complement the already established continuous trading intraday market with three pan-European implicit auctions to price cross-zonal capacity (ACER, (2019)). The main reason for this decision is that with auctions, all offers and bids are gathered and cleared simultaneously. If capacity constraints are represented in the market clearing, cross-zonal capacity scarcity (if there is one) is reflected in the values of the cleared trades. The payment to the capacity owner is the difference between consumers' and generators' payments, and this payment may create a financial incentive for capacity owners to either release capacity for intraday trade or to invest in actions that enhance intraday cross-zonal capacity.

Given that there will be intraday auctions, the following important questions arise:

- How many intraday auctions should there be per day? Should there be a small number of large auctions, or very fast and frequent auctions? Generally speaking, maximum efficiency is attainable in large auctions, where many bids and offers are optimized simultaneously. Hence, we can argue in favor of having a few sequential and large intraday auctions. In contrast to continuous trading, however, this design would postpone some of the potential trades until the next auction, and this deferral might either deprive the less flexible providers from participating in the intraday market at their latest possible time, or prevent intermittent generators from immediate self-balancing, when updated information is available (Henriot (2012a) and Hagemann (2013a)). Even though fast and frequent auctions may allow instant response to new information, they may unintentionally clear sub-optimal trades, because a better trade could have been cleared later, if we had waited for more bids and offers. However, if uncleared submitted bids and offers can be transferred to the next auction, such that potentially valuable trades are not wasted, the efficiency of this design may improve.
- What is the optimal timing of the added auctions? Should they run before, after, in parallel, or even without a continuous trading intraday market? Two important factors play a role in deciding about the timing of an auction, i.e. the share of uncertain production and the flexibility of the system to respond to this uncertainty. Henceforth, in the following we focus on the timing of an intraday auction and the two essential factors that affect this decision.

With more intermittent generators being integrated into the power system, accurate forecasting systems become increasingly valuable, since large forecasting errors can lead to major economic inefficiencies due to non-optimal schedules. NREL (2012) analyzes the wind forecast error distributions in several electrical systems, at two different time scales, i.e. day-ahead and hour-ahead, which are both important when planning unit commitment and dispatch. It is shown that shorter term forecasts, that are utilized in intraday markets, have smaller forecasting errors than day-ahead forecasts, and therefore by introducing intraday markets, only the smaller short term forecast errors must be balanced by flexibility providers in real time. Fabbri et al. (2005), Graeber et al. (2010) and Monteiro et al. (2009) also show that when getting closer to the delivery time, the wind power forecast errors, and therefore uncertainty, is declining.

Contrary to the reduced uncertainty, when approaching the delivery time, the flexibility of the power system decreases, and therefore the costs of adjusting plans increase. Figure 4.1 compares the operating cost and operational flexibility for different power plant technologies (adapted from Kleit et al. (2006)). As the figure shows, on the one side, hydroelectric generators can ramp up/down in only a few minutes, and with very low cost, while on the other side, nuclear power plants are not able to change their schedules for many days. NETL (2012) also shows how short-term deviations from initial plans can enforce extra cost on conventional power plants. Hentschel et al. (2016) develop a flexibility evaluation tool for conventional power plants, which translates a change in technical parameters to an economic effect and revenue. By having access to such tools, generators, as well as flexible consumers, are able to show their flexibility capability in various markets, by means of different cost and benefit functions. All the mentioned references emphasize that the further we move away from the day-ahead market, towards the delivery time, the higher costs are required for altering our initial position. However, this cost function is not increasing continuously. Over some periods, waiting may have little or even no impact on flexibility costs, while over other periods, many sources of flexibility may become unavailable.

Hence, the decline in uncertainty and incline in flexibility cost over time demonstrate a trade-off between postponing dispatch until the uncertainty from generation of stochastic producers is reduced, and hastening dispatch to avoid rising flexibility costs associated with changes in production and consumption on short notice. This trade-off, which is displayed in Figure 4.2, demonstrates that early market clearing results in scheduling of cheap base load power plants under high uncertainty, while later market clearing has little uncertainty but higher generation costs.

In this paper, we address the question of when, during the time between a day-ahead and a real-time market, it is best to add an intraday auction, given the trade-off between uncertainty and flexibility cost. Hence, we consider a sequential three-settlement electricity market, composed of a day-ahead, an intraday, and a real-time market. Three potential points in time (i.e. hours) are investigated for the intraday market. For the sake of simplicity, the following assumptions have been made:

- It is assumed that the day-ahead market is cleared at time 24:00 of day $d-1$ for delivery hour 24:00 of day d, i.e. we consider load and generation volumes for a single hour 24 hours ahead. Then deviations from the day-ahead production and consumption schedules are cleared at one of the potential hours for the intraday market, i.e. hours 6:00, 12:00 or 18:00 of day d, taking into account the information available at the time of the intraday market. Finally, the energy imbalances are settled by a real-time market for delivery time 24:00, some minutes before hour 24:00, when all uncertainty regarding generation from stochastic sources is resolved.
- Our model is similar to the conventional dispatch model in Morales et al. (2014) and the myopic model in Bjorndal et al. (2018). However, contrary to their conventional two-stage models (consisting of day-ahead

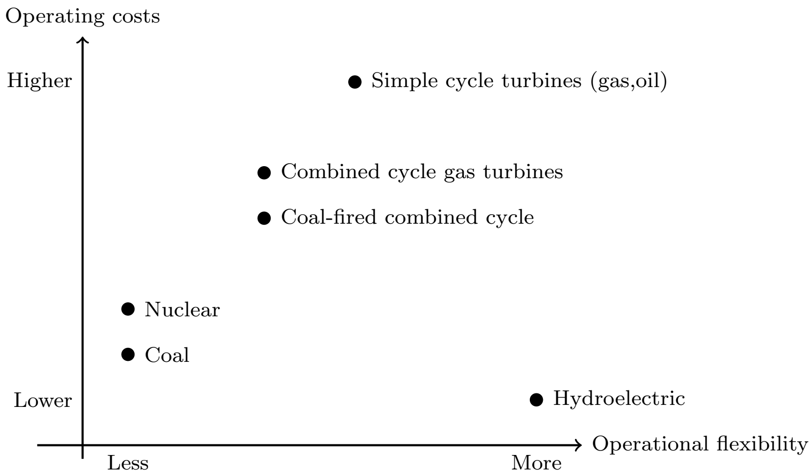


Figure 4.1. Comparison of operating cost and operational flexibility for different power plant technologies (most renewables are excluded since their operational flexibility is partly dependent on prevailing weather conditions such as irradiance and wind speed/direction)

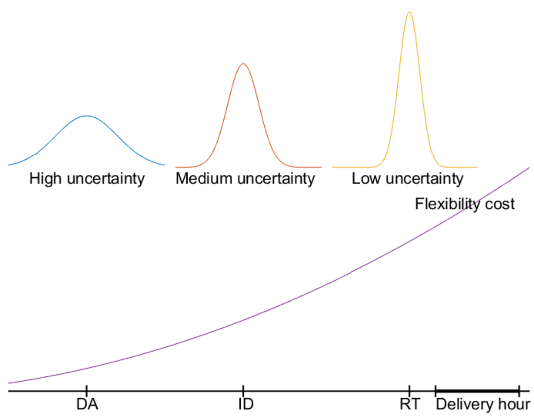


Figure 4.2. Trade-off between uncertainty and flexibility cost

and real-time), we analyze the conventional three-stage model, when production is uncertain and flexibility is costly. In conventional dispatch models the uncertainty is captured by a deterministic approach, where the day-ahead and intraday schedules of stochastic producers are constrained to their expected generation. In contrast to the stochastic dispatch models, where the effect of decisions in later markets can be reflected on the former markets by recourse, in conventional models the day-ahead decision is independent of intraday and real-time decisions, and similarly, intraday decisions are made irrespective of real-time decisions. Hence, conventional models are usually computationally tractable at the cost of suboptimal solutions.

- Even though pricing of cross-zonal capacity is an important reason for adding intraday auctions, network constraints are neglected in this paper. Our main aim here is to analyze the impact of adding an extra auction on the total cost of the system, and network constraints could easily be incorporated.

The rest of the paper is structured as follows. Section 4.2 briefly reviews the literature about intraday auctions and timing issues in the power market. In Section 4.3, the mathematical models of sequential markets are described, and these models will be tested on a numerical example explained in Section 4.4. In Section 4.5, two approaches for scenario generation are explained. Section 4.6 presents the results for the numerical example on different scenario trees, and finally, conclusions are given in Section 4.7.

4.2 Literature review

Neuhoff et al. (2016a) point to the advantages of adding multiple intraday auctions to the existing markets, considering eight criteria such as improving market liquidity, facilitating contracting for flexibility, allowing effective participation of players of all scales and technologies, ensuring technical feasibility, compatibility with current continuous trading, ensuring consistency between intraday and balancing, allowing for pricing and efficient usage of cross-zonal capacities, and finally, reducing unannounced loop flows. Due to the mentioned benefits, intraday auctions make up an important step to enhance efficiency and to reduce the operational cost of the European power system. In parallel, they empirically assess how adding auctions to the continuous intraday trading can improve the performance of the market. In Neuhoff et al. (2016c) the effect of adding the 3 pm local auction (for quarters in Germany in December 2014 at the European Power Exchange (EPEX SPOT)) to the current continuous trading is investigated. They find that the additional auction enhances liquidity, gives rise to a higher market depth and to reduced price volatility.

Similar to Neuhoff et al. (2016a), NVE THEMA Consulting Group (2019) analyzes how the various intraday market designs, including one or more auctions alongside or instead of continuous intraday trading, affect market efficiency by investigating eight mechanisms such as simultaneous clearing of multiple bids, revenues for cross-zonal capacity, providing focal points for trade, pay-as-clear pricing, timing of trade, bid structures, transaction and staffing costs and hedging quality. With respect to all these characteristics, they conclude that the introduction of intraday auctions entails the potential to support efficiency. They are, however, more vague about the number of auctions and the way they are organized alongside continuous trading.

In addition to the papers that emphasize the role of intraday auctions, other papers focus on the timing of power markets, considering the large scale integration of renewables. For instance, Borggrefe and Neuhoff (2011) state that in spite of the substantial improvement in wind forecasting methods, the day-ahead forecast is still not able to capture the increasing uncertainty due to the surging intermittent generation in the European power system. Therefore, by reducing the lead-time for wind forecasts through introducing intraday markets, it is possible to improve wind forecasts within the hours between the day-ahead and real-time. However, the new design (including intraday) has to satisfy six criteria, such as facilitating system-wide intraday adjustments, allowing co-optimization of energy and reserve services, allowing inter-temporal optimization of energy and reserve, benefiting from international integration of power systems, integrating demand side into intraday and real-time, and lastly, effective monitoring of market power.

Schroder and Weber (2011) is the only reference we have found that focuses mainly on the optimal power market timing for wind energy with respect to the trade-off between wind uncertainty and flexibility cost. The three different timing options -changing the gate closure horizon, changing the trading period length, and shifting the trading period- are conceptually analyzed for the day-ahead market. In their model, at first the hourly forecast error that needs to be corrected is quantified, then they are multiplied by flexibility costs of the 5 different scenarios (on flexibility costs) and finally the savings for wind power generation are calculated with respect to the three timing options. To the best of our knowledge, no previous paper has quantitatively and analytically examined the optimal timing of an intraday auction in the presence of wind uncertainty and flexibility costs. For a specific delivery hour, the day-ahead economic dispatch problem with expected wind power at delivery hour is optimized. Then for an intraday auction at three places optimal re-adjustments are done to correct expected wind deviations from day-ahead market. Likewise, the final optimal reschedule is done in real-time to cope with the real wind deviations from intraday. Consistent to this structure, several 5-stage scenario trees on expected (at day-ahead and intraday stage) and real (at real-time stage) wind power are tested to find the optimal intraday timing. Our scenario tree generation approach is specifically practical for sequential markets that are clearing with the expected wind power, not the wind power itself. Hence, this is also another contribution of this paper.

4.3 Mathematical model

4.3.1 Notation

The model has a set I of participants, either generators or consumers. For each $i \in I$, the variables x_i^{DA}, $x_{i,\omega^{ID}}^{ID}$ and $x_{i,\omega^{RT}}^{RT}$ represent generation or consumption quantities for the day-ahead, intraday, and real-time markets, respectively. Positive values represent generation, while negative values represent consumption.

FS_i^1 represents the set of feasible solutions corresponding to participant i for the day-ahead market. For the intraday market, the feasible set $FS_i^2(\omega^{ID}, x_i^{DA})$ depends on the intraday scenario $\omega^{ID} \in \Omega^{ID}$ as well as decision x_i^{DA} from the day-ahead market. Finally, for the real-time market, the feasible set $FS_i^3(\omega^{RT}, x_i^{DA}, x_{i,\omega^{ID}}^{ID})$ depends on the realized scenario $\omega^{RT} \in \Omega^{RT}$ and decisions x_i^{DA} and x_i^{ID} from the day-ahead and intraday markets, respectively.

A feasible solution (x_i^{DA}, x_i^{ID} and x_i^{RT}) for all three stages must satisfy the following constraints:

$$x_i^{DA} \in FS_i^1 \qquad i \in I \tag{4.1}$$

$$x_{i,\omega^{ID}}^{ID} \in FS_i^2(\omega^{ID}, x_i^{DA}) \qquad i \in I, \omega^{ID} \in \Omega^{ID} \tag{4.2}$$

$$x_{i,\omega^{RT}}^{RT} \in FS_i^3(\omega^{RT}, x_i^{DA}, x_i^{ID}) \qquad i \in I, \omega^{RT} \in \Omega^{RT} \tag{4.3}$$

Each market participant i is located in a specific node $n \in N$, and we let I^n denote the set of generators / consumers located in node n. Nodes of the network are connected by a set of physical transmission lines. Since in this paper we are focusing on the impact of having three sequential markets, the congestion management issues will be neglected.

4.3.2 Day-ahead market (first stage)

The day-ahead market clearing model identifies the optimal schedule x_i^{DA} that minimizes day-ahead generation cost of the system as follows:

$$\text{Minimize}_{x,\tau} \qquad \sum_{i \in I} C_i^{DA}(x_i^{DA}) \tag{4.4a}$$

$$\text{subject to:} \qquad \tau_n + \sum_{i \in I^n} x_i^{DA} = 0 \qquad n \in N \tag{4.4b}$$

$$\sum_{n \in N} \tau_n = 0 \tag{4.4c}$$

$$x_i^{DA} \in FS_i^1 \qquad i \in I \tag{4.4d}$$

For each market participant i, there is a linear day-ahead marginal cost or benefit function $a_i + b_i x_i^{DA}$ with non-negative parameters a_i and b_i. For a consumer, as mentioned in Section 4.3.1, we have $x_i^{DA} < 0$, and the corresponding curve $a_i + b_i x_i$ will therefore have a downward slope. The total day-ahead cost/benefit curve, which can be derived from the marginal cost/benefit curve, is a quadratic function

$$C_i^{DA}\left(x_i^{DA}\right) = a_i x_i^{DA} + \frac{1}{2} b_i {x_i^{DA}}^2.$$

The number τ_n is the net inflow of power in node n from the network. Therefore, constraints (4.4b) enforce the day-ahead balancing conditions at each node, stating that the power generation plus the net power flow equals the demand at each node. The equality (4.4c) states that the total generation must be equal to the total demand in the whole network, i.e. we consider a lossless system. Constraints (4.4d) represents feasibility constraints for generators and consumers, e.g., capacity limits, non-negativity constraints on generation and negativity constraints on consumption variables. In particular, we assume that the day-ahead quantity for the stochastic generators G_{ST} is constrained by

$$0 \leqslant x_i^{DA} \leqslant \hat{x}_i^{DA} \qquad i \in G_{ST}, \tag{4.5}$$

e.g., it must be a non-negative quantity less than or equal to the forecasted (expected) generation $\hat{x}_i^{DA}$. Since the marginal cost of a stochastic generator $i \in G_{ST}$ is usually lower than for the conventional generators, and given that there are not any other binding constraints, the stochastic generator will often be dispatched at its forecasted capacity, i.e., $x_i^{DA} = \hat{x}_i^{DA}$.

4.3.3 Intraday market (second stage)

Once the day-ahead schedule x_i^{DA} has been obtained from (4.4), an intraday auction allows market participants to adjust their physical positions closer to the real-time with respect to their updated forecast at intraday time. All intraday parameters and decision variables are augmented with the scenario subscript ω^{ID}. For generator $i \in G_{ST}$, let $\hat{x}_{i,\omega^{ID}}^{ID}$ denote the forecasted generation at delivery time, as seen at intraday time in scenario ω^{ID}. Over- or underestimation at former stage(s) (day-ahead market) may result in different actions at intraday:

- Overestimation ($\hat{x}_i^{DA} > \hat{x}_{i,\omega^{ID}}^{ID}$): The stochastic generator may have to buy back power that it has sold in the day-ahead market, i.e., $x_i^{DA} - x_{i,\omega^{ID}}^{ID} > 0$.
- Underestimation ($\hat{x}_i^{DA} < \hat{x}_{i,\omega^{ID}}^{ID}$): The stochastic generator may be able to sell extra power in the intraday market, i.e., $x_i^{DA} - x_{i,\omega^{ID}}^{ID} < 0$.

If the scheduled generation by stochastic generators G_{ST} is increased, i.e., $\sum_{i \in G_{ST}} (x_{i,\omega^{ID}}^{ID} - x_i^{DA}) > 0$, then this may be compensated by other agents in the following ways:

- The power produced by flexible generators can be reduced. In market terms, this means that the generators that are flexible in the intraday market, $i \in G_{flex}^{ID}$, buy back a certain amount $x_{i,\omega^{ID}}^{ID^{buy}}$ of energy in the intraday market.
- The power consumed by consumers that are elastic in the intraday market, $i \in D_{elastic}^{ID}$, can be increased. In other words, elastic demands can buy a certain amount $x_{i,\omega^{ID}}^{ID^{buy}}$ of energy in the intraday market.

Likewise, if the scheduled generation by stochastic generators is reduced, i.e., $\sum_{i \in G_{ST}} (x_{i,\omega^{ID}}^{ID} - x_i^{DA}) < 0$, then this may be compensated by other agents in the following ways:

- Increase the power production of flexible generators, $i \in G_{flex}^{ID}$, this implies that flexible generators sell an additional amount $x_{i,\omega^{ID}}^{ID^{sell}}$ of energy in the intraday market.
- Reduce the power consumed by elastic demands, $i \in D_{elastic}^{ID}$, which is equivalent to say that flexible demands can sell a certain amount $x_{i,\omega^{ID}}^{ID^{sell}}$ of energy in the intraday market.

For each intraday scenario ω^{ID} a revised schedule $x_{\omega^{ID}}^{ID}$ for the delivery hour is found by solving the following optimization problem:

$$
\begin{aligned}
&\text{Minimize}_{x^{ID},\tau} && \sum_{i \in I} \Big(C_i^{DA}(x_{i,\omega^{ID}}^{ID}) + C_i^{ID}(x_{i,\omega^{ID}}^{ID^{buy}}, x_{i,\omega^{ID}}^{ID^{sell}}) \Big) && && \text{(4.6a)} \\
&\text{subject to:} && \tau_n + \sum_{i \in I^n} x_{i,\omega^{ID}}^{ID} = 0 && n \in N && \text{(4.6b)} \\
& && \sum_{n \in N} \tau_n = 0 && && \text{(4.6c)} \\
& && x_{i,\omega^{ID}}^{ID} \in FS_i^2(\omega^{ID}, x_i^{DA}) && i \in I && \text{(4.6d)} \\
& && x_{i,\omega^{ID}}^{ID} = x_i^{DA} + x_{i,\omega^{ID}}^{ID^{sell}} - x_{i,\omega^{ID}}^{ID^{buy}} && i \in G_{flex}^{ID} \cup D_{elastic}^{ID} && \text{(4.6e)} \\
& && x_{i,\omega^{ID}}^{ID^{sell}} \geqslant 0, x_{i,\omega^{ID}}^{ID^{buy}} \geqslant 0 && i \in G_{flex}^{ID} \cup D_{elastic}^{ID} && \text{(4.6f)}
\end{aligned}
$$

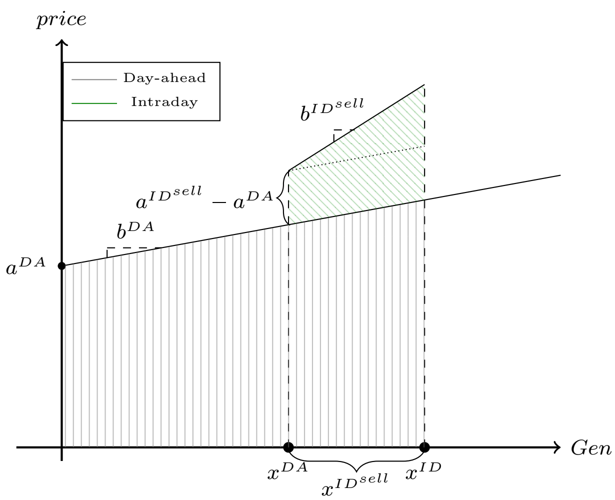
Similar to the day-ahead market clearing model in (4.4), the constraints (4.6b) and (4.6c) enforce the intraday balancing conditions at each node and the energy balance for the entire network, respectively. Constraint (4.6d), similar to (4.4d), represents feasibility constraints for generators and consumers, e.g., non-negativity (for $x_{i,\omega^{ID}}^{ID}$, $i \in G_{flex}^{ID}$) / negativity constraints (for $x_{i,\omega^{ID}}^{ID}$, $i \in D_{elastic}^{ID}$) and capacity constraints. Note that the feasible set $FS_i^2(\omega^{ID}, x_i^{DA})$ depends on the current intraday scenario ω^{ID} as well as the day-head schedule x_i^{DA}. In particular, as in (4.5), we assume that the revised schedule after the intraday market is constrained by a capacity equal to the forecasted (expected) generation:

$$
0 \leqslant x_{i,\omega^{ID}}^{ID} \leqslant \hat{x}_{i,\omega^{ID}}^{ID} \qquad i \in G_{ST} \qquad \text{(4.7)}
$$

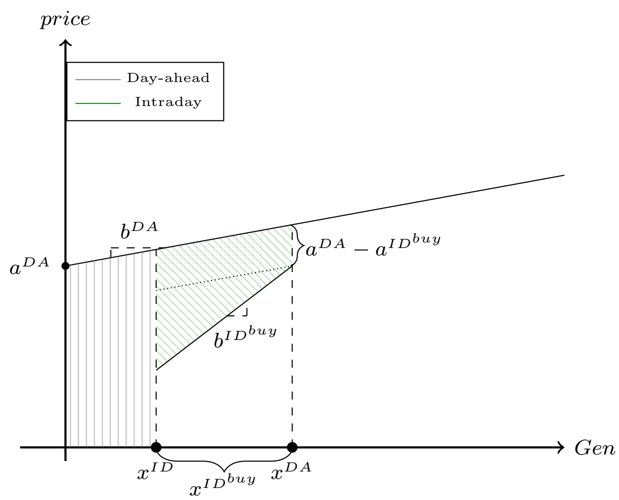
Constraints (4.6e)-(4.6f) defines the buy and sell quantities in the intraday market, i.e., the changes relative to the day-ahead schedule.

The objective function (4.6a) represents the total cost of dispatching participants in both day-ahead and intraday markets, provided that the intraday schedule initiated from the day-ahead schedule. The first term $C_i^{DA}(x_{i,\omega^{ID}}^{ID})$ is the total cost (sum of both markets) for generator/consumer i evaluated at the day-ahead cost parameters, while the additional flexibility cost caused by rescheduling (buy/sell) in the intraday market is given by (4.8),

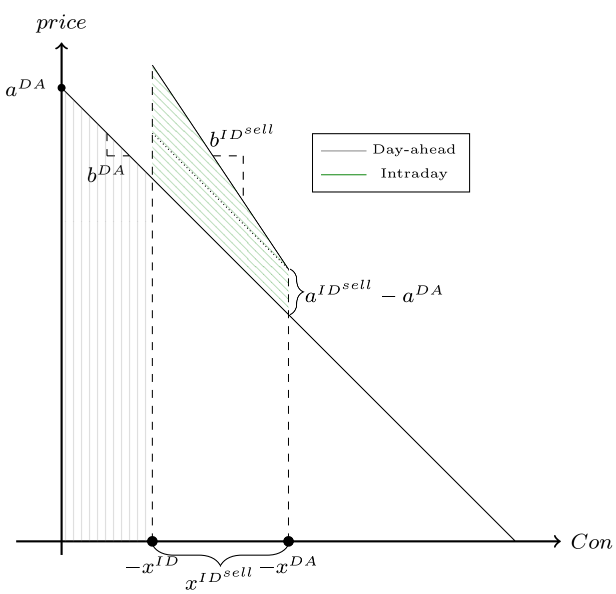
$$\begin{aligned} C_i^{ID}(x_{i,\omega^{ID}}^{ID^{buy}}, x_{i,\omega^{ID}}^{ID^{sell}}) = (a_i^{ID^{sell}} - a_i^{DA})\ x_{i,\omega^{ID}}^{ID^{sell}} + \frac{1}{2}(b_i^{ID^{sell}} - b_i^{DA})(x_{i,\omega^{ID}}^{ID^{sell}})^2 \\ +(a_i^{DA} - a_i^{ID^{buy}})\ x_{i,\omega^{ID}}^{ID^{buy}} + \frac{1}{2}(b_i^{ID^{buy}} - b_i^{DA})(x_{i,\omega^{ID}}^{ID^{buy}})^2 \end{aligned} \tag{4.8}$$



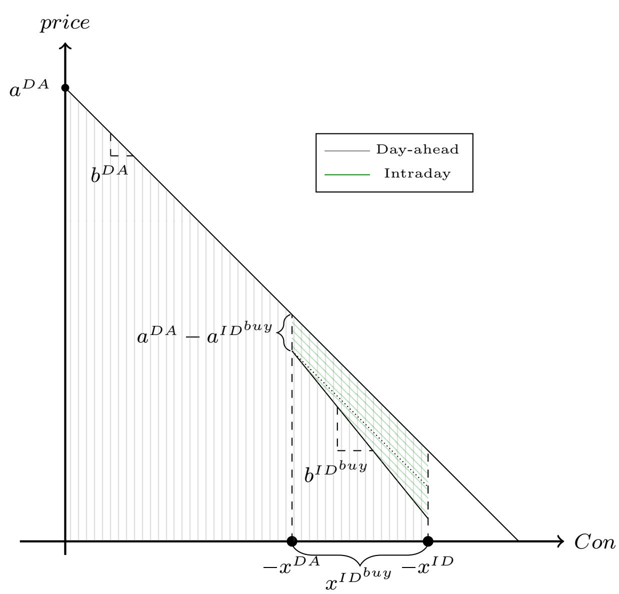
(a) Sell in intraday market for generator i



(b) Buy in intraday market for generator i



(c) Sell in intraday market for consumer i



(d) Buy in intraday market for consumer i

Figure 4.3. Supply and demand curves in intraday market

The extra flexibility costs are reflected by cost and benefit function parameters that differ from those in the day-ahead formulation (4.4). For any flexible participant i, there are parameters $a_i^{ID^{sell}}$ and $b_i^{ID^{sell}}$ for the intraday sell curve and $a_i^{ID^{buy}}$ and $b_i^{ID^{buy}}$ for the intraday buy curve, where $a_i^{ID^{buy}} \leqslant a_i \leqslant a_i^{ID^{sell}}$ and $b_i \leqslant \min\{b_i^{ID^{buy}}, b_i^{ID^{sell}}\}$. The objective function (4.6a) is illustrated by the grey and green areas in Figure 4.3. Areas with vertical grey lines represent the value of $C_i^{DA}(x_{i,\omega^{ID}}^{ID})$, while the parallelograms and triangles with diagonal green lines represent the flexibility cost $C_i^{ID}(x_{i,\omega^{ID}}^{ID^{buy}}, x_{i,\omega^{ID}}^{ID^{sell}})$.

4.3.4 Real-time market (the third stage)

The production and consumption quantities scheduled in markets prior to the balancing market can substantially deviate from the actual production and consumption at the real time. This is specifically evident in markets with a high share of stochastic production. Thus, the real-time market closes the balance gap between the other prior markets and real-time energy delivery. Therefore, this is the last market opportunity to balance production and consumption.

Let the optimal day-ahead schedule x_i^{DA} and optimal intraday adjustment $x_{i,\omega^{ID}}^{ID}$ (that involves $x_{i,\omega^{ID}}^{sell}$ or $x_{i,\omega^{ID}}^{buy}$) be obtained from optimization problems (4.4) and (4.6). Hence, decisions at this stage depend on the potential stochastic production $\hat{x}_{i,\omega^{RT}}^{RT}$ as well as the first stage decision x_i^{DA} and the second stage decision $x_{i,\omega^{ID}}^{ID}$. Therefore, the potential energy imbalance for a stochastic generator i is given by $\hat{x}_{i,\omega^{RT}}^{RT} - x_{i,\omega^{ID}}^{ID}$, and the total imbalance in the system equals $\sum_{i \in G_{ST}} (\hat{x}_{i,\omega^{RT}}^{RT} - x_{i,\omega^{ID}}^{ID})$. Like in the intraday market, this imbalance could be positive, which illustrates surplus of generation, or negative, implying a shortage of generation. A generation surplus can be handled by:

- Reducing the power generated by flexible generators $i \in G_{flex}^{RT}$ by down-regulation or buying back a certain amount $x_{i,\omega^{RT}}^{dn}$ energy in the balancing market.
- Increasing the power consumption of elastic demands $i \in D_{elastic}^{RT}$ by down-regulation or buying a certain amount $x_{i,\omega^{RT}}^{dn}$ of energy in the balancing market.
- Spilling a part $x_{i,\omega^{RT}}^{spill}, i \in G_{ST}$ of the stochastic production (However, stochastic generation is usually spilled due to network congestion but since in this paper network constraints have not been considered, we do not model spillage as well).

Similarly, a shortage of power can be handled by:

- Increasing the power generated by flexible generators $i \in G_{flex}^{RT}$ by up-regulation or selling a certain amount $x_{i,\omega^{RT}}^{up}$ of energy in the balancing market.
- Decreasing the power consumption of elastic demands $i \in D_{elastic}^{RT}$ by up-regulation or selling a certain amount $x_{i,\omega^{RT}}^{up}$ of energy in the balancing market.
- Shed a part $x_{i,\omega^{RT}}^{shed}, i \in D_{inelastic}^{RT}$ of the inelastic demand with a very high value of lost load (VOLL).

As indicated previously in Section 4.3.3, all real-time decision variables x_i^{up}, x_i^{dn} ($i \in G_{flex}^{RT}$ or $i \in D_{elastic}^{RT}$) and x_i^{shed} ($i \in D_{inelastic}^{RT}$) must be subscripted by ω^{RT} to indicate the realization $\hat{x}_{i,\omega^{RT}}^{RT}$ of stochastic production. Consequently, in the real-time market, for every scenario $\omega^{RT} \in \Omega^{RT}$, the following optimization problem is solved to minimize the cost of correcting energy imbalances, provided that the real-time decision initiated from the optimal intraday market decision x^{ID} :

$$\underset{\substack{x^{RT}, x^{up}, x^{dn} \\ x^{shed}, x^{spill}, \tau}}{\text{Minimize}} \quad \sum_{i \in I} (C_i^{DA}(x_{i,\omega^{RT}}^{RT}) + C_i^{ID}(x_{i,\omega^{ID}}^{sell}, x_{i,\omega^{ID}}^{buy}, x_{i,\omega^{RT}}^{up}, x_{i,\omega^{RT}}^{dn}) +$$

$$C_i^{RT}(x_{i,\omega^{RT}}^{up}, x_{i,\omega^{RT}}^{dn})) + \sum_{i \in D_{inelast}^{RT}} VOLL_i \cdot x_{i,\omega^{RT}}^{shed} \tag{4.9a}$$

$$\text{subject to:} \quad \tau_n + \sum_{i \in n} x_{i,\omega^{RT}}^{RT} = 0 \qquad n \in N \tag{4.9b}$$

$$\sum_{n \in N} \tau_n = 0 \tag{4.9c}$$

$$x_{i,\omega^{RT}}^{RT} \in FS_i^3(\omega^{RT}, x_i^{DA}, x_i^{ID}) \qquad i \in I \tag{4.9d}$$

$$x_{i,\omega^{RT}}^{RT} = x_i^{DA} + x_{i,\omega^{ID}}^{sell} - x_{i,\omega^{ID}}^{buy} + x_{i,\omega^{RT}}^{up} - x_{i,\omega^{RT}}^{dn} \qquad i \in G_{flex}^{RT} \cup D_{elastic}^{RT} \tag{4.9e}$$

$$x_{i,\omega^{ID}}^{up}, x_{i,\omega^{ID}}^{dn} \geqslant 0 \qquad i \in G_{flex}^{RT} \cup D_{elastic}^{RT} \tag{4.9f}$$

$$x_{i,\omega^{RT}}^{RT} \leqslant \hat{x}_{i,\omega^{RT}}^{RT} \qquad i \in G_{ST} \tag{4.9g}$$

$$x_{i,\omega^{RT}}^{RT} = x_i^{DA} + x_{i,\omega^{RT}}^{shed} \qquad i \in D_{inelast}^{RT} \tag{4.9h}$$

$$x_{i,\omega^{ID}}^{shed} \geqslant 0 \qquad i \in D_{inelast}^{ID} \cap D_{inelast}^{RT} \tag{4.9i}$$

Similar to the day-ahead and intraday market clearing model in (4.4) and (4.6), the constraints (4.9b) and (4.9c) enforce the intraday balancing conditions at each node and the energy balance for the entire network, respectively. Constraint (4.9d), similar to (4.4d) and (4.6d), represents feasibility constraints for generators and consumers, e.g., non-negativity (for $x_{i,\omega^{RT}}^{RT},\ i \in G_{flex}^{RT}$) / negativity constraints (for $x_{i,\omega^{RT}}^{RT},\ i \in D_{elastic}^{RT}$) and capacity constraints. Note that the feasible set $FS_i^3(\omega^{RT}, x_i^{DA}, x_i^{ID})$ depends on the current real-time scenario ω^{RT} as well as the day-head and intraday schedules x_i^{DA} and x_i^{ID}.

Constraints (4.9e)-(4.9f) define the up and down regulation quantities in the real-time market, i.e., the changes relative to the day-ahead schedule x_i^{DA} and intraday schedule x_i^{buy} or x_i^{sell}. Constraints (4.9g) show that the final schedule of stochastic generator i at the end of the real-time market cannot be more than its real generation. For those consumers that are inelastic in both day-ahead and intraday markets, in case that day-ahead allocated demand cannot be satisfied, part of the load can be shed by constraints (4.9h)-(4.9i) but with very high value of lost load cost, VOLL (the reason $x_{i,\omega^{RT}}^{shed}$ is added to x_i^{DA}, instead of being subtracted, is that x_i^{DA} is assumed to be negative for consumers).

Flexible generators and elastic demands are assumed to be less available and more costly in the real-time market than in the day-ahead and intraday markets. For any market participant i which is flexible in real-time ($i \in G_{flex}^{RT}$ or $i \in D_{elastic}^{RT}$) there are parameters $a_i^{RT^{up}}$ and $b_i^{RT^{up}}$ for up-regulation and $a_i^{RT^{dn}}$ and $b_i^{RT^{dn}}$ for down-regulation in the real-time market, such that $a_i^{RT^{up}} \geqslant a_i^{ID^{sell}} \geqslant a_i^{DA} \geqslant a_i^{ID^{buy}} \geqslant a_i^{RT^{dn}}$, $b_i^{DA} \leqslant b_i^{ID^{buy}} \leqslant \min\{b_i^{RT^{up}}, b_i^{RT^{dn}}\}$, and $b_i^{DA} \leqslant b_i^{ID^{sell}} \leqslant \min\{b_i^{RT^{up}}, b_i^{RT^{dn}}\}$.

The objective (4.9a) of the real-time market clearing is to minimize the cost of correcting imbalances with respect to the previous markets dispatches. We can explain the objective function as the sum of three terms, given by (4.10), (4.11), and (4.12). The first term $C_i^{DA}(x_{i,\omega^{RT}}^{RT})$ is the total cost of generation and consumption for the final dispatch $x_{i,\omega^{RT}}^{RT}$ evaluated at the day-ahead cost parameters. The extra flexibility cost from intraday and real-time rescheduling, evaluated at intraday parameters, is given by $C_i^{ID}(x_{i,\omega^{ID}}^{sell}, x_{i,\omega^{ID}}^{buy}, x_{i,\omega^{RT}}^{up}, x_{i,\omega^{RT}}^{dn})$, while

$C_i^{RT}(x_{i,\omega^{RT}}^{up}, x_{i,\omega^{RT}}^{dn})$ is the additional cost of real-time redispatch evaluated at the real-time cost parameters.

As previously mentioned, in this paper which is in line with the current European sequential market design, when we are at the intraday and real-time stages, we know the value of x_i^{DA}. Hence, in all equations (4.6)-(4.13), x_i^{DA} is a known value, and not a variable. By the same logic, $x_{i,\omega^{ID}}^{sell}$ and $x_{i,\omega^{ID}}^{buy}$ are known values at the real-time stage equations (4.9)-(4.13). Therefore, in order to formulate (4.11) and (4.12), instead of using binary variables, we are able to use the indicator function $\gamma(\cdot)$ for $x_{i,\omega^{ID}}^{sell}$ and $x_{i,\omega^{ID}}^{buy}$, where $\gamma(u) = 1$ for $u \neq 0$ and $\gamma(u) = 0$ for $u = 0$.

$$C_i^{DA}(x_{i,\omega^{RT}}^{RT}) = a_i^{DA}\left(x_i^{DA} + x_{i,\omega^{ID}}^{ID^{sell}} - x_{i,\omega^{ID}}^{ID^{buy}} + x_{i,\omega^{RT}}^{RT^{up}} - x_{i,\omega^{RT}}^{RT^{dn}}\right) \tag{4.10a}$$

$$+\frac{1}{2}b_i^{DA}\left(x_i^{DA} + x_{i,\omega^{ID}}^{ID^{sell}} - x_{i,\omega^{ID}}^{ID^{buy}} + x_{i,\omega^{RT}}^{RT^{up}} - x_{i,\omega^{RT}}^{RT^{dn}}\right)^2 \tag{4.10b}$$

$$C_i^{ID}\left(x_{i,\omega^{ID}}^{sell}, x_{i,\omega^{ID}}^{buy}, x_{i,\omega^{RT}}^{up}, x_{i,\omega^{RT}}^{dn}\right) =$$

$$\left(a_i^{ID^{sell}}\gamma(x_{i,\omega^{ID}}^{sell}) + a_i^{ID^{buy}}\gamma(x_{i,\omega^{ID}}^{buy}) - a_i^{DA}\right)\left(x_{i,\omega^{ID}}^{ID^{sell}} - x_{i,\omega^{ID}}^{ID^{buy}} + x_{i,\omega^{RT}}^{RT^{up}} - x_{i,\omega^{RT}}^{RT^{dn}}\right) \tag{4.11a}$$

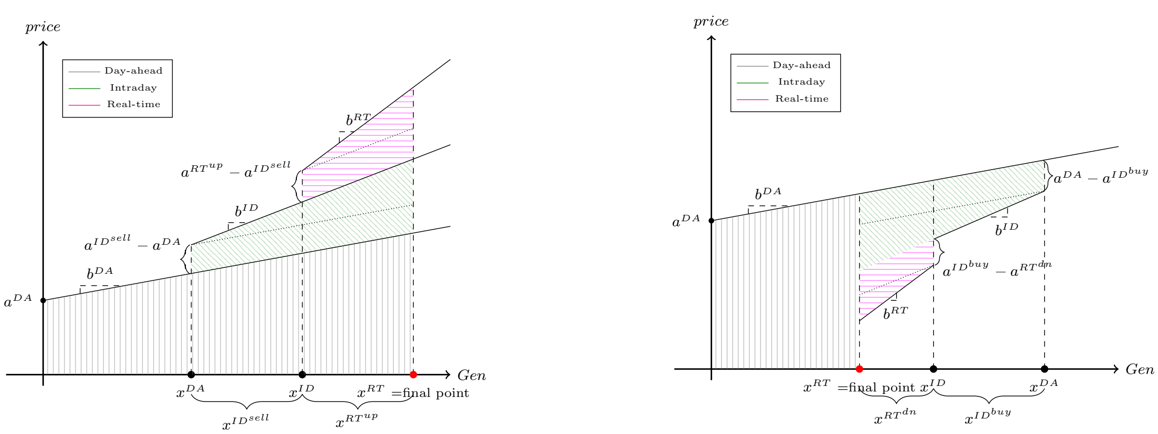
$$+\frac{1}{2}\left(b_i^{ID^{sell}}\gamma(x_{i,\omega^{ID}}^{sell}) + b_i^{ID^{buy}}\gamma(x_{i,\omega^{ID}}^{buy}) - b_i^{DA}\right)\left(x_{i,\omega^{ID}}^{ID^{sell}} - x_{i,\omega^{ID}}^{ID^{buy}} + x_{i,\omega^{RT}}^{RT^{up}} - x_{i,\omega^{RT}}^{RT^{dn}}\right)^2 \tag{4.11b}$$

$$C_i^{RT}\left(x_{i,\omega^{RT}}^{up}, x_{i,\omega^{RT}}^{dn}\right) = \left(a_i^{RT^{up}} - a_i^{ID^{sell}}\gamma(x_{i,\omega^{ID}}^{sell}) - a_i^{ID^{buy}}\gamma(x_{i,\omega^{ID}}^{buy})\right)x_{i,\omega^{RT}}^{RT^{up}} \tag{4.12a}$$

$$+\left(a_i^{ID^{sell}}\gamma(x_{i,\omega^{ID}}^{sell}) + a_i^{ID^{buy}}\gamma(x_{i,\omega^{ID}}^{buy}) - a_i^{RT^{dn}}\right)x_{i,\omega^{RT}}^{RT^{dn}} \tag{4.12b}$$

$$+\frac{1}{2}\left(b_i^{RT^{up}} - b_i^{ID^{sell}}\gamma(x_{i,\omega^{ID}}^{sell}) - b_i^{ID^{buy}}\gamma(x_{i,\omega^{ID}}^{buy})\right)\left(x_{i,\omega^{RT}}^{RT^{up}}\right)^2 \tag{4.12c}$$

$$+\frac{1}{2}\left(b_i^{RT^{dn}} - b_i^{ID^{sell}}\gamma(x_{i,\omega^{ID}}^{sell}) - b_i^{ID^{buy}}\gamma(x_{i,\omega^{ID}}^{buy})\right)\left(x_{i,\omega^{RT}}^{RT^{dn}}\right)^2 \tag{4.12d}$$



(a) Sell in intraday and up-regulate in real-time.

(b) Buy in intraday and down-regulate in real-time.

Figure 4.4. Two simple cases for the cost function (4.9a).

In order to explain the functions (4.10), (4.11), and (4.12), for the case of a flexible generator, we use the diagrams in Figures 4.4 and 4.5. Figure 4.4a illustrates the case where the generator sells additional power in the intraday market and up-regulates even further in the real-time market. The final real-time volume is then $x^{RT} = x^{DA} + x^{ID^{sell}} + x^{RT^{up}}$. The cost of this volume evaluated at day-ahead parameter values is represented by the grey vertically hatched area, which consists of the area of a rectangle (4.10a) plus the area of a triangle (4.10b), with $x^{ID^{buy}} = x^{RT^{dn}} = 0$. The extra flexibility cost of intraday and real-time redispatch is given by the dotted green area, i.e., the sum of the area of the parallelogram (4.11a) plus the area of a triangle (4.11b). Since $x^{ID^{buy}} = x^{RT^{dn}} = 0$, (4.11a) is equal to $(a_i^{ID^{sell}} - a_i^{DA})(x_{i,\omega^{ID}}^{ID^{sell}} + x_{i,\omega^{RT}}^{RT^{up}})$ and (4.11b) is equal to $\frac{1}{2}(b_i^{ID^{sell}} - b_i^{DA})(x_{i,\omega^{ID}}^{ID^{sell}} + x_{i,\omega^{RT}}^{RT^{up}})^2$. Finally, the pink horizontally hatched area represents the extra cost of real-time redispatch at real-time cost parameters, and is again given by the sum of the area of a parallelogram (4.12a) and the area of a triangle (4.12c). Note that, since $x^{ID^{buy}} = x^{RT^{dn}} = 0$, (4.12a) equals $(a_i^{RT^{up}} - a_i^{ID^{sell}})x_{i,\omega^{RT}}^{RT^{up}}$, (4.12c) equals $\frac{1}{2}(b_i^{RT^{up}} - b_i^{ID^{sell}})(x_{i,\omega^{RT}}^{RT^{up}})^2$, and both (4.12b) and (4.12d) evaluate to zero.

Figure 4.4b illustrates the case where a generator buys back power in the intraday market and down-regulates even further in the real-time market. The final real-time volume is $x^{RT} = x^{DA} - x^{ID^{buy}} - x^{RT^{dn}}$, and $x^{ID^{sell}} = x^{RT^{up}} = 0$. The cost of the real-time volume evaluated at day-ahead parameter values is represented by the grey vertically hatched area, which again consists of the area of a rectangle (4.10a) plus the area of a triangle (4.10b). The extra flexibility cost of intraday and real-time redispatch is given by the dotted green area, i.e., the sum of the area of the parallelogram (4.11a) plus the area of a triangle (4.11b). Finally, the pink horizontally hatched area represents the extra cost of real-time redispatch at real-time cost parameters, and is again given by the sum of the area of a parallelogram (4.12b) and the area of a triangle (4.12d). Note that, since $x^{ID^{buy}} = x^{RT^{dn}} = 0$, both (4.12a) and (4.12c) have values equal to zero.

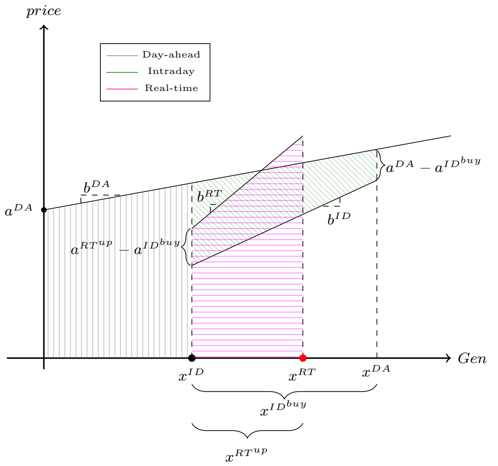
The more complex cases, where the changes made in the intraday market and the real-time market go in opposite directions, are illustrated in Figure 4.5. The case where $x^{ID^{sell}} = x^{RT^{dn}} = 0$ and $x^{ID^{buy}} > x^{RT^{up}}$ is illustrated in Figures 4.5a and 4.5b. The final real-time quantity is $x^{RT} = x^{DA} - x^{ID^{buy}} + x^{RT^{up}}$, and Figure 4.5a illustrates the cost adjustments that results from the intraday and real-time generation quantity adjustments. The gray vertically-hatched area is the cost of the intraday schedule evaluated at day-ahead cost parameters, and the green dotted area is the extra flexibility cost that results from the intraday adjustment and the assumption that not all day-ahead costs are reversible. Then, the generation quantity is upregulated in the real-time market, and this adjustment results in an extra cost given by the horizontally-hatched pink area. The final cost for this case can also be shown as in Figure 4.5b, which is directly related to (4.10), (4.11) and (4.12). The gray vertically hatched area is the cost of the final schedule, evaluated at day-ahead cost parameters, and given by the area of a parallellogram (4.10a) and a triangle (4.10b). The green dotted area, with a value equal to the sum of (4.11a) and (4.11b), represents the value of the net adjustment made intraday and real-time, evaluated at intraday cost parameters. Note that the value of (4.11a), given by $(a_i^{ID^{buy}} - a_i^{DA})(-x_{i,\omega^{ID}}^{ID^{buy}} + x_{i,\omega^{RT}}^{RT^{up}})$, is positive, since $a_i^{ID^{buy}} < a_i^{DA}$ and $x_{i,\omega^{ID}}^{ID^{buy}} > x_{i,\omega^{RT}}^{RT^{up}}$. Hence, since (4.11b) is non-negative, the total value of (4.11) is positive. Finally, the pink horizontally-hatched area shows the extra flexibility cost resulting from the real-time up-regulation, and given by the sum of (4.12a) and (4.12c). Since $x^{RT^{dn}} = 0$, the remaining two terms in (4.12) will evaluate to zero.

The case where $x^{ID^{sell}} = x^{RT^{dn}} = 0$ and $x^{ID^{buy}} < x^{RT^{up}}$ is illustrated in Figures 4.5c and 4.5d. Again, the final real-time quantity is $x^{RT} = x^{DA} - x^{ID^{buy}} + x^{RT^{up}}$, and Figure 4.5c illustrates the cost adjustments that results from the intraday and real-time generation quantity adjustments. As in the previous case, the figure shows the cost of the intraday schedule evaluated at day-ahead cost parameters (vertically-hatched gray area), the extra flexibility cost that results from the intraday adjustment (green dotted area), and the extra cost resulting from the real-time up-regulation (horizontally-hatched pink area). Figure 4.5d illustrates how the total cost for this case is related to (4.10), (4.11) and (4.12). Again, the gray vertically hatched area is the cost of the final schedule, evaluated at day-ahead cost parameters, and given by (4.10), and the pink horizontally-hatched area represents the extra flexibility cost resulting from the real-time up-regulation, given by the sum of (4.12a) and (4.12c). The green checkered area represents the value of the net adjustment resulting from the intraday and real-time market clearing, evaluated at intraday cost parameters. In this case, the value of (4.11a), given by $(a_i^{ID^{buy}} - a_i^{DA})(-x_{i,\omega^{ID}}^{ID^{buy}} + x_{i,\omega^{RT}}^{RT^{up}})$, is negative, since $a_i^{ID^{buy}} < a_i^{DA}$ and $x_{i,\omega^{ID}}^{ID^{buy}} < x_{i,\omega^{RT}}^{RT^{up}}$. The total value of (4.11) may be positive or negative, depending on the relative magnitudes of the negative term (4.11a) and the non-negative term (4.11b). In the example shown in Figure 4.5d, the net value, as indicated by the green checkered area, is negative. Note that the green checkered area is included both in (4.10) and (4.12), so the negative adjustment given by (4.11) avoids double-counting.

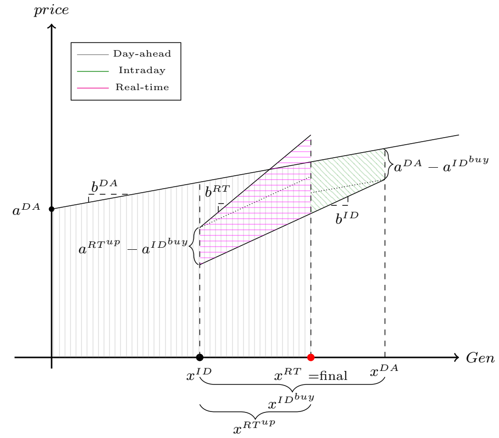
Finally, Figures 4.5e and 4.5f illustrate the case where $x^{ID^{buy}} = x^{RT^{up}} = 0$ and $x^{RT} = x^{DA} + x^{ID^{sell}} - x^{RT^{dn}}$. Again, the vertically-hatched areas represent the value of (4.10), i.e., the cost of the real-time dispatch at day-ahead cost parameters. The green dotted area in Figure 4.5e and the green checkered area in Figure 4.5f represent the value of (4.11), i.e., the cost adjustment due to the net generation quantity adjustments in the intraday and real-time markets, evaluated at intraday cost parameters. The value of (4.11a) is $(a_i^{ID^{sell}} - a_i^{DA})(x_{i,\omega^{ID}}^{ID^{sell}} - x_{i,\omega^{RT}}^{RT^{dn}})$, where $a_i^{ID^{sell}} > a_i^{DA}$. This value is positive in Figure 4.5e and negative in Figure 4.5f. The deduction in the latter case serves to avoid double-counting of the green checkered area. Finally, the horizontally-hatched areas in both figures represent the extra flexibility cost caused by the down-regulation in the real-time market.

By summing (4.10), (4.11) and (4.12) and doing some simplifications, the general formula for (4.9a) can be written as (4.13) below. We prove the equality given by (4.13) in Appendix A.

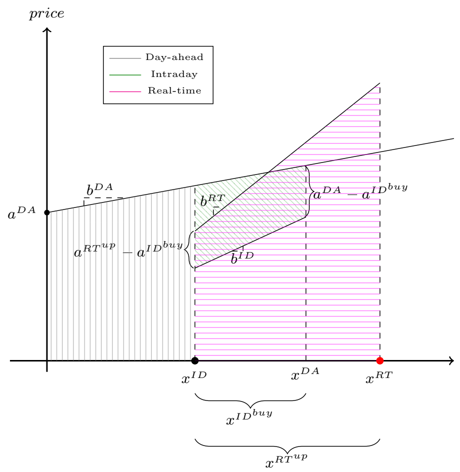
$$
\begin{aligned}
&C_i^{DA}(x_{i,\omega^{RT}}^{RT}) + C_i^{ID}\left(x_{i,\omega^{ID}}^{sell}, x_{i,\omega^{ID}}^{buy}, x_{i,\omega^{RT}}^{up}, x_{i,\omega^{RT}}^{dn}\right) + C_i^{RT}\left(x_{i,\omega^{RT}}^{up}, x_{i,\omega^{RT}}^{dn}\right)\\
&= a_i^{DA} x_i^{DA} + a_i^{ID^{sell}} x_{i,\omega^{ID}}^{ID^{sell}} - a_i^{ID^{buy}} x_{i,\omega^{ID}}^{ID^{buy}} + a_i^{RT^{up}} x_{i,\omega^{RT}}^{RT^{up}} - a_i^{RT^{dn}} x_{i,\omega^{RT}}^{RT^{dn}}\\
&+ \frac{1}{2} b_i^{DA}(x_i^{DA} + x_{i,\omega^{ID}}^{ID^{sell}} - x_{i,\omega^{ID}}^{ID^{buy}} + x_{i,\omega^{RT}}^{RT^{up}} - x_{i,\omega^{RT}}^{RT^{dn}})^2\\
&+ \frac{1}{2}\Big[(b_i^{ID^{sell}} - b_i^{DA})\; x_{i,\omega^{ID}}^{ID^{sell}2} + (b_i^{ID^{buy}} - b_i^{DA})\; x_{i,\omega^{ID}}^{ID^{buy}2}\\
&+ (b_i^{RT^{up}} - b_i^{DA})\; x_{i,\omega^{RT}}^{RT^{up}2} + (b_i^{RT^{dn}} - b_i^{DA})\; x_{i,\omega^{RT}}^{RT^{dn}2}\Big]\\
&+ (b_i^{ID^{sell}} - b_i^{DA})\; x_{i,\omega^{ID}}^{ID^{sell}}\; (x_{i,\omega^{RT}}^{RT^{up}} - x_{i,\omega^{RT}}^{RT^{dn}})\\
&- (b_i^{ID^{buy}} - b_i^{DA})\; x_{i,\omega^{ID}}^{ID^{buy}}\; (x_{i,\omega^{RT}}^{RT^{up}} - x_{i,\omega^{RT}}^{RT^{dn}})
\end{aligned}
\tag{4.13}
$$



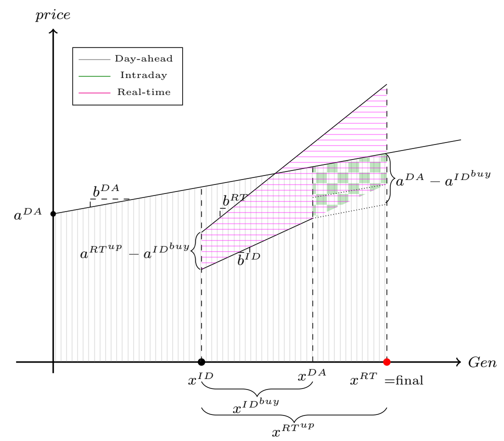
(a) Buy and up-regulate, with $x^{ID^{buy}} > x^{RT^{up}}$. Step-wise illustration of ID and RT adjustments.



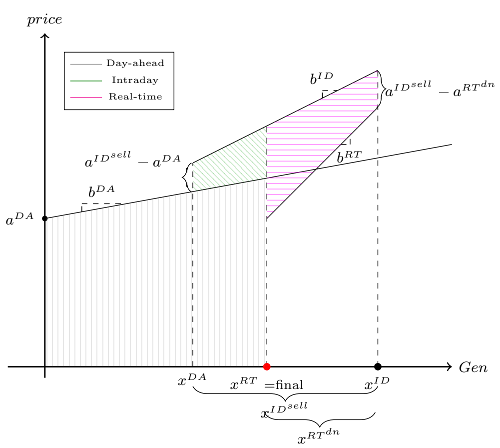
(b) Buy and up-regulate, with $x^{ID^{buy}} > x^{RT^{up}}$.



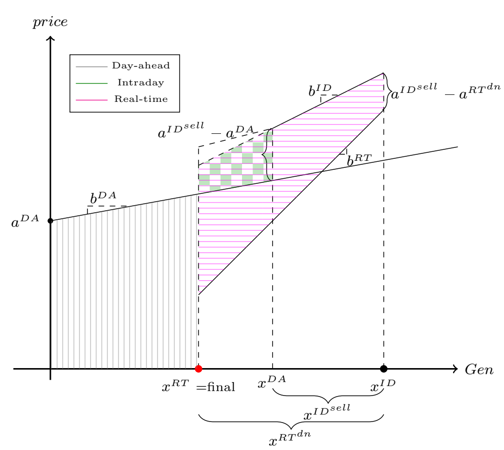
(c) Buy and up-regulate, with $x^{ID^{buy}} < x^{RT^{up}}$. Step-wise illustration of ID and RT adjustments.



(d) Buy and up-regulate, with $x^{ID^{buy}} < x^{RT^{up}}$.



(e) Sell and down-regulate, with $x^{ID^{sell}} > x^{RT^{dn}}$.



(f) Sell and down-regulate, with $x^{ID^{sell}} < x^{RT^{dn}}$.

Figure 4.5. Complex cases for the cost function (4.9a).

4.4 Numerical example

In order to illustrate how we can analyze the optimal timing of an intraday auction, we use a simple example with an uncongested network, with two nodes and a single line, as illustrated in Figure 4.6. This small system consists of two loads, d_1 and d_2, one wind power plant, WP, and two conventional generators, g_1 and g_2. Loads are assumed to be inelastic and equal to 5000 and 7000 MW, respectively, however it is possible to shed load at a cost of 1000 $\$/MWh$. We assume that the marginal cost of wind power is zero and that the capacity is 5700 MW. Since conventional generators are assumed to have positive marginal cost, the wind power generator will always be dispatched up to the quantity that is bid into a market. Wind generation at node 1 is the only source of uncertainty, and we assume that this uncertainty can be characterized by a finite set of scenarios. These scenarios then represent all possible wind power realizations. Scenario generation approaches are described in more detail in Section 4.3. Since the actual wind power availability in real time is uncertain when the day-ahead and intraday market offers are submitted, we need an assumption about how the wind power generator bids into these markets. In our analyses we assume that the wind power generator bids to adjust its production plan to the expected wind power available in real time at all market stages. Moreover, we assume that the wind power generator can adjust its production without any extra cost, thus it may sell/buy in intraday and up/down regulate in real time at zero cost, but it must respect the expected power constraints at the time of the intraday auction, and the realized power constraints given by the scenarios in real time. Hence, the wind generator is partly flexible.

The conventional generator, g_1, is relatively cheap, but is inflexible, and will therefore just participate in the day-ahead market and not in the intraday and real-time markets. On the other hand, generator g_2 is flexible to participate in all these markets but is more expensive and mostly used for flexibility purposes. The day-ahead, intraday and real-time cost parameters of the conventional generators are displayed in Table 4.1.

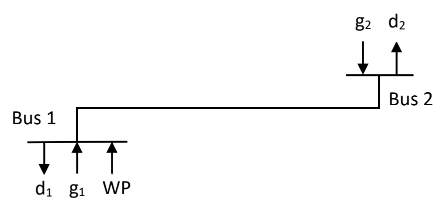


Figure 4.6. Two-bus power system

Table 4.1. Conventional power plant data

	node	x^{max}	C^{DA}	C^{ID_1}	C^{ID_2}	C^{ID_3}	C^{RT}
g_1	1	5000	10	-	-	-	-
g_2	2	9000	40	40+$a^{ID_1^{sell}}$ 40-$a^{ID_1^{buy}}$	40+$a^{ID_2^{sell}}$ 40-$a^{ID_2^{buy}}$	40+$a^{ID_3^{sell}}$ 40-$a^{ID_3^{buy}}$	40+$a^{RT^{up}}$ 40-$a^{RT^{dn}}$

C^{DA} is the offer price for energy sales in the day-ahead market. In the example, we assume that g_1 and g_2 submit their constant marginal costs to the day-ahead market. Moreover, g_2 is the only flexible source that can be rescheduled to balance uncertain wind production, and this flexibility imposes additional costs compared to being dispatched in the day-ahead market. In order to simplify, we assume constant increments/decrements in the marginal cost over time for g_2, reflecting flexibility costs. Thus, the slopes of the respective cost curves are all set to zero. Hence, $b_{g_2}^{ID_k^{sell}} = b_{g_2}^{ID_k^{buy}} = b_{g_2}^{RT^{up}} = b_{g_2}^{RT^{dn}} = 0, k = 1,2,3$, where the index k represents intraday auctions at three different points in time. Thus, flexibility costs in intraday and real time are incorporated by increasing or decreasing the intercept of these market cost curves relative to the intercept for the day-ahead market, i.e.

$$
\begin{aligned}
a_{g_2}^{ID_1^{sell}} &= a_{g_2}^{DA} + \Delta a_{g_2}^{ID_1^{sell}}, & \Delta a_{g_2}^{ID_1^{sell}} &\geqslant 0\\
a_{g_2}^{ID_2^{sell}} &= a_{g_2}^{DA} + \Delta a_{g_2}^{ID_2^{sell}}, & \Delta a_{g_2}^{ID_2^{sell}} &\geqslant \Delta a_{g_2}^{ID_1^{sell}}\\
a_{g_2}^{ID_3^{sell}} &= a_{g_2}^{DA} + \Delta a_{g_2}^{ID_3^{sell}}, & \Delta a_{g_2}^{ID_3^{sell}} &\geqslant \Delta a_{g_2}^{ID_2^{sell}}\\
a_{g_2}^{RT^{up}} &= a_{g_2}^{DA} + \Delta a_{g_2}^{RT^{up}}, & \Delta a_{g_2}^{RT^{up}} &\geqslant \Delta a_{g_2}^{ID_3^{sell}}\\
a_{g_2}^{ID_1^{buy}} &= a_{g_2}^{DA} - \Delta a_{g_2}^{ID_1^{buy}}, & \Delta a_{g_2}^{ID_1^{buy}} &\geqslant 0\\
a_{g_2}^{ID_2^{buy}} &= a_{g_2}^{DA} - \Delta a_{g_2}^{ID_2^{buy}}, & \Delta a_{g_2}^{ID_2^{buy}} &\geqslant \Delta a_{g_2}^{ID_1^{buy}}\\
a_{g_2}^{ID_3^{buy}} &= a_{g_2}^{DA} - \Delta a_{g_2}^{ID_3^{buy}}, & \Delta a_{g_2}^{ID_3^{buy}} &\geqslant \Delta a_{g_2}^{ID_2^{buy}}\\
a_{g_2}^{RT^{dn}} &= a_{g_2}^{DA} - \Delta a_{g_2}^{RT^{dn}}, & \Delta a_{g_2}^{RT^{dn}} &\geqslant \Delta a_{g_2}^{ID_3^{buy}}
\end{aligned}
$$

The increasing/decreasing trend in Δa is reflecting the increasing flexibility costs when getting closer to delivery time. In Section 4.6, we experiment with different flexibility costs, i.e. values for Δa, to see how it affects the best timing of an intraday auction.

4.5 Representing uncertainty and information in scenario trees

Uncertainty in wind power generation is best characterized by continuous stochastic variables, however, in order to keep the problem tractable, we represent this uncertainty, as well as how information is revealed over time, by using scenario trees. The scenarios, given by the information along the paths of the scenario trees, are subsequently used together with the market clearing models in Section 4.3, to assess the effect on social welfare by placing an intraday auction at different points in time. Uncertainty in wind power generation is often quantified by a probability distribution for wind power resources or for forecast errors. We may, however, also consider a conditional probability distribution for wind power generation at a given future point in time, given the information up until the present point in time. This may be especially fruitful in the context of this paper, since we are studying a sequential market, where new information about the wind power generation at a specific future delivery time becomes available as we move closer to real time. This means that we may first condition the probability distribution on the information available at the time of the day-ahead auction, and then, as the information is updated over time, so is the conditional probability distribution. In real time, wind resources are given, and there is no uncertainty left.

In the following, we examine two ways to generate scenario trees. First, we construct some simple illustrative scenario trees, with characteristics mimicking those of the conditional probability distributions obtained by Pritchard (2011), who is using quantile-type models to construct short term probabilistic forecasts, the simplest models having present power as the only input. Secondly, we use data from the Nordic power market to find scenarios of short-term wind power production, based on the method described in Pinson et al. (2009). The simulated data is transformed to a scenario tree.

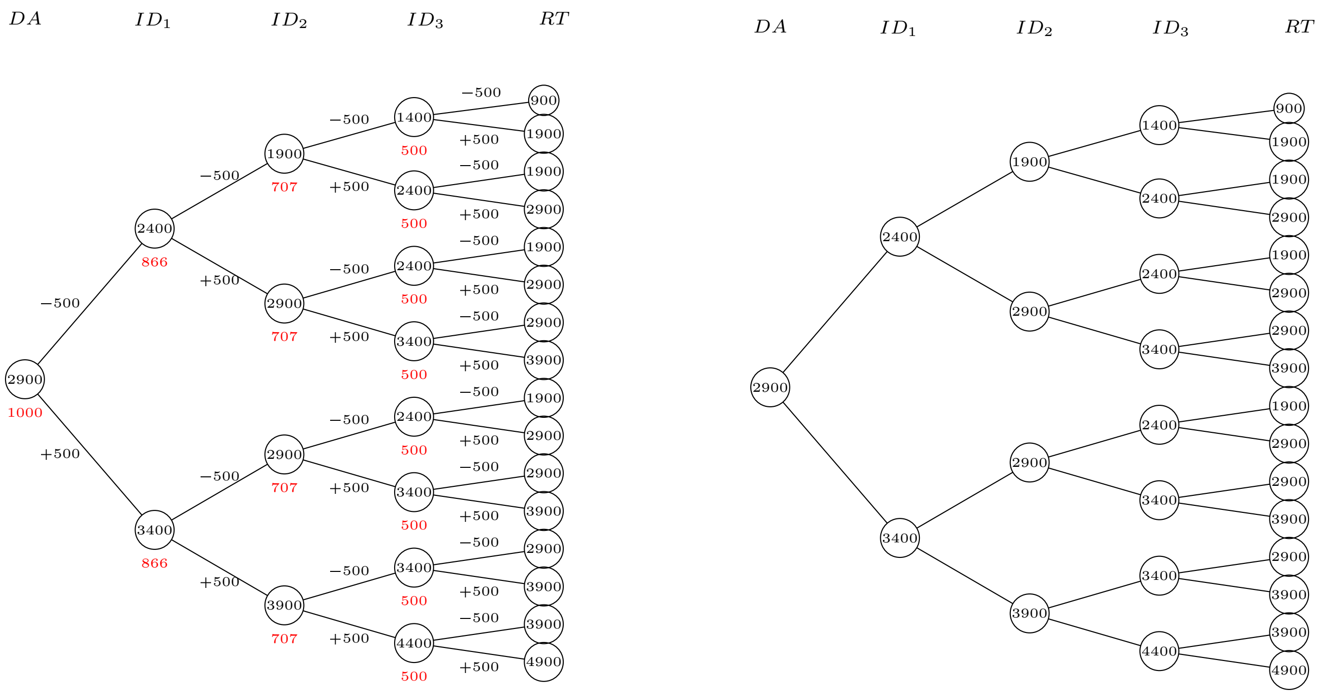
4.5.1 Scenarios inspired by Pritchard (2011)

Pritchard (2011) studies the conditional distribution of wind power available at a specific time in the future, given information available at the present. In the simplest model, termed a "probabilistic-persistence" quantile forecast, the only information used as input to the model is the present wind power. Analyzing data from New Zealand wind farms in this setting, Pritchard (2011) finds that the shapes of the conditional distributions of future available power depends on whether the present wind is high or low. If, for instance, present power is low (high), then the probability distribution is skewed towards positive (negative) changes in available power, while if the present power is at a medium level, the probability distribution is more bell shaped, i.e. the probability of having positive and negative changes of the same magnitudes are about the same, and the probability of a small or zero change is highest, i.e persistence.

Pritchard (2011) estimates quantiles of the conditional distributions by means of quantile regression. An interesting observation is that there is considerably less variation in half-hour forecasts compared to 2-hour forecasts, and this is illustrated by the quantiles being closer together in the half-hour forecasts than in the 2-hour forecasts. This is exactly the basis for the trade-off that we are interested in in this paper, namely that when placing an intraday auction between day-ahead and real time, we must make a trade-off between reducing the effects of uncertainty by running the auction close to real time, and reducing flexibility costs by running the auction close to day-ahead, when quantity adjustments are cheaper and/or more generators and loads can contribute.

For the numerical examples in Section 4.6, we use two stylized scenario trees, depicted in Figures 4.7 and 4.8, that exhibit some of the characteristics of the conditional probability distributions estimated by Pritchard (2011). The starting node of the scenario tree shows the actual wind power available at the day-ahead stage (i.e. time 0:00). We assume that it is about half the capacity of the wind power generator in our numerical example, i.e. 2900 MW. From this point, we assume two possible (and equally probable) changes in available power for hour 6:00. For simplicity, we assume all changes to be +/- 500 MW throughout the tree. Thus, the conditional probability distribution of changes in power, 18 hours ahead in time, is assumed to be uniform, with only two possible outcomes, +/- 500 MW. The available power in hour 6:00 is shown in stage 2 in the tree in Figure 4.7a. These values can be interpreted as the actual power in hour 6:00 when we move forward along the paths in the tree from the nodes in stage 2. Again, we assume that power will increase or decrease by 500 MW until hour 12:00, hence 4 scenarios are generated for stage 3, two from each starting node at stage 2. By repeating this procedure for every 6 hour, 16 wind scenarios will be generated for the delivery hour at 24:00. Each scenario, corresponding to a path in the tree, shows the power available for delivery in hour 24:00, but also how the available power develops over time, at each 6-hour stage.

By moving forward in the tree, and getting closer to the delivery time, more information is revealed about which scenario is going to be realized. For instance, at the time of clearing the day-ahead market, we do not have any information about which of the 16 scenarios will be more likely at hour 24:00. However, if an intraday market is cleared after 6 hours, the power information at hour 6:00 determines whether the upper or the lower scenario has been realized. If the upper scenario is realized at hour 6:00, at hour 24:00 only the eight upper leaf nodes can be realized, thus the eight lower leaf nodes can be excluded from investigation. At each node in the tree we calculate the standard deviation of the available power at each leaf node that is connected to the node in question. These numbers are given in red, and we notice that the standard deviations are reduced when we come closer to the delivery time.



(a) Symmetric power now tree

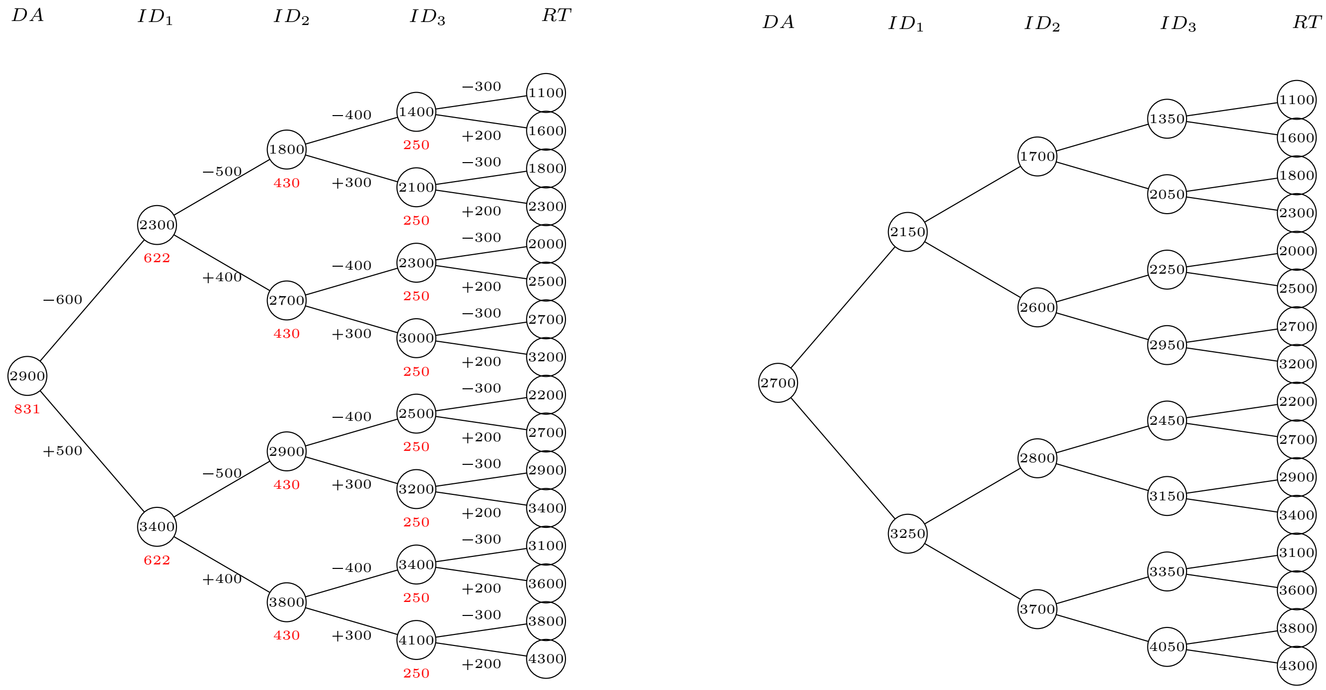
(b) Expected tree for (a)

Figure 4.7. Symmetric scenario tree with corresponding conditional expectations

The procedure for generating the scenarios in Figure 4.7 is based on an assumption that we have accessible conditional probability distributions for available wind power 6 hours ahead, given the actual power now. In general, available wind power at a future point in time depends on other factors as well, including meteorological variables such as wind speed, wind direction, air pressure, seasonal and diurnal indicators etc. (Pritchard (2011)). In a more realistic setting, these factors could be considered when generating scenarios. Since we are only considering adding one intraday auction, another way to generate scenario trees would be to combine 24-hour, 18-hour, 12-hour and 6-hour horizon forecast data, depending on where the intraday auction is placed (i.e. ID_1, ID_2, or ID_3). In a more realistic setting, we should add an additional stage in the beginning of the scenario tree, in order to consider different wind power possibilities at the day-ahead stage, however, for simplicity we consider only one day-ahead alternative.

Since we have assumed that the wind power producer bids the expected power at the delivery time, conditional on the most updated information, to each sequential market, it is useful to note the expected available wind power in real time at each node in the scenario tree. While the tree on the left hand side in Figure 4.7 is generated to produce leaf nodes that reflect possible wind power realizations in real time, the tree on the right hand side shows conditional expectations of available wind power in real time, i.e. the number in each node, at each stage, shows the expected power in the leaf nodes that are connected to this node.

As mentioned previously, we have used equal increments and decrements of 500 MW at all stages in the tree in Figure 4.7. One drawback of this is that we have several nodes with the same power quantity at each stage in the tree. For instance, 4 out of the 16 scenarios have 1900 MW wind power in real time. In order to avoid this situation, we will also test the asymmetric tree in Figure 4.8.



(a) Asymmetric power now tree

(b) Expected tree for (a)

Figure 4.8. Asymmetric scenario tree with corresponding conditional expectations

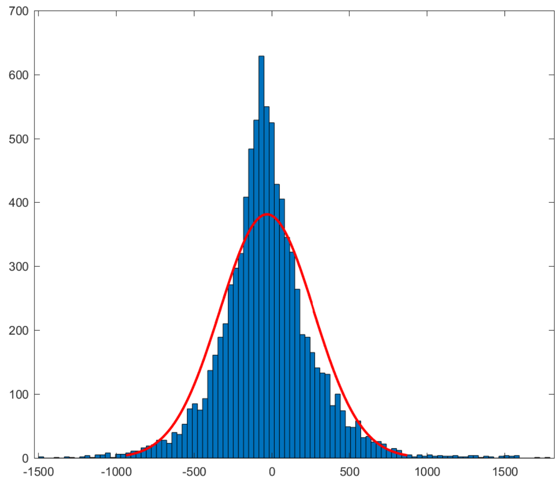
4.5.2 Scenarios based on the method by Pinson et al. (2009)

4.5.2.1 Data

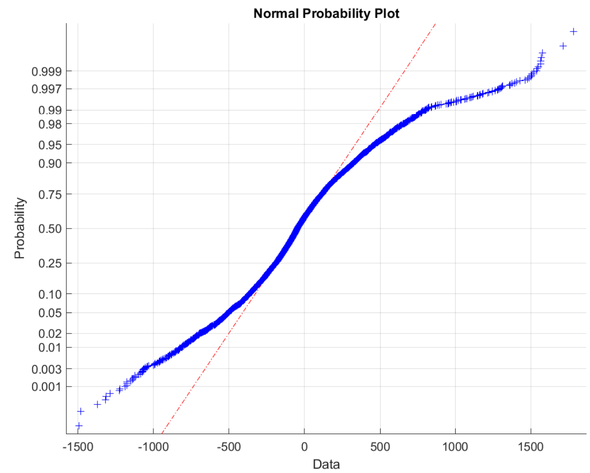
We assume that the wind power capacity of the numerical example equals to the cumulative wind capacity of Denmark at the end of 2018, 5700 MW (WindEurope (2019)). Since no public data for different wind power forecast horizons is available (it means that for each delivery hour, we just have access to the 24-hour ahead forecast not anything in between), 24 hour-ahead forecast data from Nord pool is utilized. This data set is composed of the hourly real and forecast of the wind power production at Denmark for year 2018. Forecast is a $D \times T = 365 \times 24$ matrix called $F = [f_{dt}]$, means that for every hour t of each day d of year 2018, a 24-hour ahead forecast f_{dt} is available. Since real wind power production for all hours of 2018 is also available, error matrix $E_{365\times24} = [e_{dt}]$ is extractable. The hourly forecast for the next 24 hours announces at hour 00:00 which coincides with the time of our day-ahead market. The average hourly production in areas DK_1 and DK_2 in 2018 was 1571 MWh, with almost 3.2 times higher peak production, 5051 MWh.

Nord pool does not provide any other forecast horizons or update of the forecast between the day-ahead and delivery time. Indeed, by having access to the more frequent forecast horizons, more accurate scenario trees can be generated; in our case 24, 18, 12 and 6 hour horizons are required.

Figure 4.9 shows that the forecast error does not follow the normal distribution, especially the tails. However, as will be explained in Section 4.5.2.2, it can be transformed to a normally distributed stochastic process.



(a) Forecast error histogram versus fitted normal distribution



(b) Normal probability plot for forecast error

Figure 4.9. Forecast error distribution analysis

4.5.2.2 Statistical scenarios of wind power production

Most of the current wind power forecast methods provide end-users with point forecasts which is a single summary statistics for random variable $x_{i,t+k}, i \in G_{ST}$, which shows the potential wind power production at time $t + k$, where k is the forecast horizon. Even though these forecasts are sometimes enough for decision makers, they do not say anything about the uncertainty of the underlying stochastic process. In order to do that, interval forecasts or, even better, density forecasts can be used. Recently, a great effort has been made to develop such forecasts, called probabilistic forecasts. Since such forecasts are generated on a per horizon basis, they disregard the interdependence structure of forecast errors among different forecast horizons. This interdependence structure is particularly important for time-dependent and multi-stage decision making problems, such as the multi-market problem we are considering in this paper. Hence, to generate scenarios of wind power production that shows the development of wind power over all hours of look-ahead time, we have used the method devised by Pinson et al. (2009). In the following, we explain how we have implemented this method to simulate the power forecast scenarios given the forecast matrix F. Power forecast scenarios are generated by the following steps:

1. For each hour $t = 1, ..., 24$ (each column of F), estimate the cumulative distribution function (CDF) by the empirical distribution function

$$\widehat{CDF}_t(f) = \frac{\text{Number of } f_{dt} \leqslant f}{D}. \tag{4.14}$$

2. Compute

$$U_t = \widehat{CDF}_t(f_{dt}), \qquad t = 1, ..., 24 \tag{4.15}$$

Since $CDF_t(f_{dt})$ is uniformly distributed, $U(0,1)$, we get an approximate $U(0,1)$-variable by U_t.

3. Next, compute a standard normal distribution variable Z_t, $N(0,1)$, by

$$Z_t = \Phi^{-1}(U_t), \qquad t = 1, ..., 24 \tag{4.16}$$

   where Φ is the CDF for the standard normal distribution.

4. The dependence structure between the forecasts of different hours collected in the vector $\boldsymbol{Z} = [Z_t]$ is captured in the constant 24×24 variance-covariance matrix $V(\boldsymbol{Z}) = \Sigma$. The diagonal elements of Σ are all equal to one and consequently, the off-diagonal elements are correlations.

5. Now, a multivariate normal vector, $\hat{\boldsymbol{Z}} = [\hat{Z}_t]$, $t = 1, ..., 24$, with mean vector $\mathbf{0}_{24}$ and variance-covariance matrix $\Sigma_{24\times24}$ is generated. Through the next steps, by a reverse procedure we have passed so far, s forecast scenario paths will be generated.

6. We simulate $\hat{\boldsymbol{Z}} = [\hat{Z}_t]$, $t = 1, ..., 24$ from the 24-dimensional normal distribution.

7. $\hat{Z}_t$ are transformed back to a $U(0,1)$-variable by

$$\hat{U}_t = \Phi(\hat{Z}_t), \qquad t = 1, ..., 24 \tag{4.17}$$

8. A scenario path for the power forecast, drawn from the estimated distribution, with the interdependence between hours accounted for, is obtained by

$$\hat{f}_t = \widehat{CDF}_t^{-1}(\hat{U}_t), \qquad t = 1, ..., 24 \tag{4.18}$$

   It should be noted that CDF is a step function and its inverse is not unique. However, we have many data points so using, e.g., the r'th smallest value as an approximation for $\widehat{CDF}_t^{-1}(1/r)$, does not differ much from using the, say, $(r+1)$'th.

9. Finally, s scenario paths for the power forecast are generated by iterating steps 6,7 and 8.

Figure 4.10 is an example of wind power point forecast (from Nord pool data and shows the wind power forecast for 365th day of year 2018) and 30 relevant scenario paths generated from the method mentioned in Pinson et al. (2009). These scenarios reflect the forecast uncertainty as well as the interdependence structure of forecast errors and describe how much wind production will be at each hour of the next 24 hours.

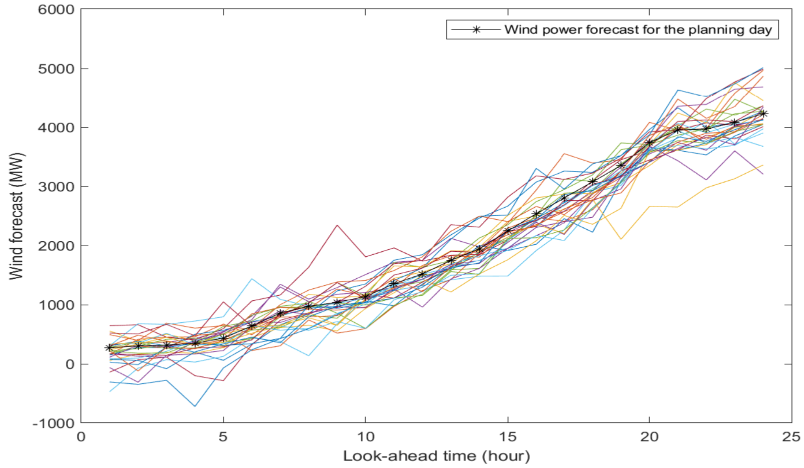


Figure 4.10. Wind power scenarios associated with point forecasts

As can be seen in Figure 4.10, scenarios follow the same trend as point forecasts. However, by moving away from hour 0:00, when the point forecasts were published for the next 24 hours, uncertainty of prediction increases. By simulating 1000 scenarios, the correlation between hours 1:00 to 23:00 with hour 24:00 (delivery hour) is measured. As Figure 4.11 demonstrates, the forecast for hours 1:00 to 13:00 have very low correlation with hour 24:00. Hence, the wind production at these hours does not contain valuable information about production at delivery hour. In other words, placing an intraday auction at these hours will not solve the problem with a high level of uncertainty even though the flexibility costs are lower.

The potential places for an intraday market must reflect different uncertainty levels. For example, hours 3:00, 5:00, 7:00 and 9:00 do not differ from an uncertainty perspective. Hence, there is no worth in comparing these alternatives. Therefore, 3 potential places 3:00, 18:00 and 21:00 are chosen based on their high, medium and low level of uncertainty, respectively with correlation coefficients 0.22, 0.42 and 0.58.

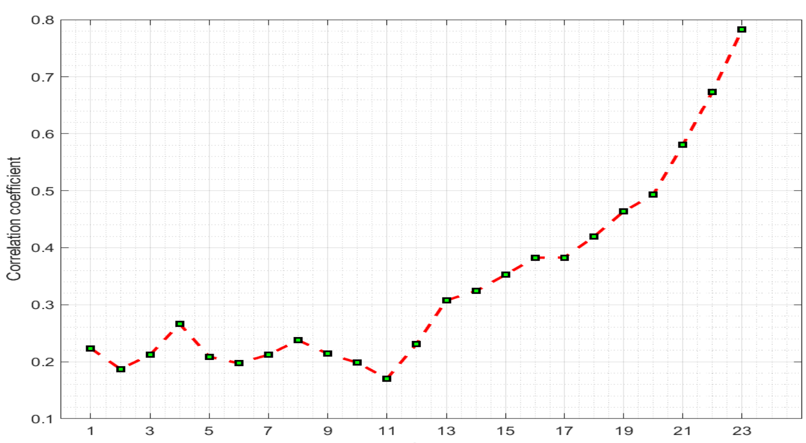


Figure 4.11. Correlation between hours 1 to 23 with hour 24

4.5.2.3 Building scenario tree by a clustering (bucketing) approach

In Section 4.5.2.2 several scenario paths were obtained by sampling from a continuous probability distribution but still additional steps are required to build a scenario tree with desirable characteristics. One of the appropriate approaches is cluster (bucket) analysis mentioned in Birge and Mulvey (1996), Canestrelli and Giove (1999) and Dupačová et al. (2000).

The 1000 scenario paths extracted from the previous section - represents that there are 1000 wind power possibilities for each hour 1:00 to 24:00- are collected in a matrix $M_{1000\times 24}$. However, we shall only consider the possible hours for the intraday market at hours 3:00, 18:00 and 21:00 and the delivery hour 24:00 (the hour that day-ahead, intraday and real-time are optimized for). Hence, columns 3, 18, 21 and 24 of matrix M are saved in matrix $M'_{1000\times 4} = [M_{(3)}, M_{(18)}, M_{(21)}, M_{(24)}]$

The outcome of this clustering approach is a 5-stage scenario tree which resembles scenario trees in Figures 4.7b and 4.8b. Each bucket is equivalent to a node in the mentioned trees. Algorithm.1 explains the bucketing approach in details.

μ of each bucket is the expected wind power ($\hat{x}_i^{DA}$ or $\hat{x}_i^{ID}$) which is directly utilized in the day-ahead or intraday market models. σ of the bucket is the standard deviation that shows the amount of uncertainty. These $sigma$'s are mostly decreasing from the parent to child buckets but not necessarily for all. The std of the day-ahead bucket equals to 339 and the std of the ID_1 buckets are equal to 325, 317, 343, 335, and 331. For ID_3 stage, the minimum and maximum stds are respectively 82 and 390 which means that at least there is one bucket which has a std higher than day-ahead bucket. To sum up, with the available data set, we ended up with a scenario tree with decreasing stds for most buckets but compared to trees in Figures 4.7b and 4.8b which show a huge std reduction, the stds in this tree display a smaller reduction. However, the other important point that should be noticed here is that the 24-hour ahead forecast data is much more accurate than the other trees, because the std of the day-ahead node in data-driven tree is 339 which is much smaller than the std of the equivalent node in other trees (796, 1000 and 831, respectively for Pritchard's, asymmetric and symmetric trees).

4.6 Numerical results

In this section some computational results are presented. Sections 4.6.1 and 4.6.2 present the results and analyses related to the asymmetric and symmetric scenario trees shown in Figure 4.8b and Figure 4.7b, respectively, while the results for the data driven scenario tree, generated in Section 4.5.2, are given in Section 4.6.3.

As indicated in Table 4.1, g_2 is the only flexible generator in the system that can participate in several markets with potentially different cost parameters. In order to analyse how various cost parameters in different sequential markets impact the best intraday market placement, nine cost parameter settings for g_2 are depicted in Figure 4.12.

Figure 4.12a shows that in case 1 participation in the day-ahead market costs 40 $\$/MWh$ for g_2, and there is no additional cost for the intraday (at different hours) and real-time markets. Therefore, all $\Delta a^{ID_k^{buy}} = \Delta a^{ID_k^{sell}} = \Delta a^{RT^{up}} = \Delta a^{RT^{dn}} = 0, k = 1, 2, 3$ and $b^{DA} = b^{ID_k^{buy}} = b^{ID_k^{sell}} = b^{RT^{up}} = b^{RT^{dn}} = 0, k = 1, 2, 3$. These cost parameters may reflect a hydropower plant, with an opportunity cost of water, i.e. water value, equal to 40 $\$/MWh$ used for the the short-term generation planning, and where deviations from the schedules, even on very

Algorithm 1: Bucketing algorithm

Input : $M'_{1000\times 4}$
$\bar{b}$: number of buckets
b_{stg} : number of buckets at stage stg
s : number of scenario paths
s_{stg} : number of scenarios in each bucket of stage stg
$C_{stg,j}$: j^{th} bucket in stage stg, $j = 1, ..., b_{stg}$
$B_{stg,ch,p}$: ch^{th} child bucket of parent bucket p in stage stg, $ch = 1, ..., \bar{b}$

Initial : $s = 1000$
$\bar{b} = 5$

```
for stg = 1 to 4 do
    b_stg ← b̄^(stg−1) (5^(stg−1))
    s_stg ← s / b̄^(stg−1)
    if stg=1 then
        C_stg,1 ← M′
    end
    else
        for p = 1 to b_stg−1 do
            (B_stg,ch,p, μ(B_stg,ch,p), σ(B_stg,ch,p))=BuildBucket(C_stg−1,p)
            C_stg,ch+(p−1)b̄ ← B_stg,ch,p
        end
    end
end

Function BuildBucket(C_stg−1,p): /* Generate b̄ child buckets for parent bucket p */
    Sort C_stg−1,p based on column stg − 1
    l=1
    for ch = 1 to b̄ do
        C_stg,ch ← C_stg−1,p[l : l + s_stg − 1, 1 : 4]
        l ← l + s_stg
        μ(C_stg,ch) = EXP(C_stg,ch[:, 4]) /* EXP():Average of scenarios in the bucket */
        σ(C_stg,ch) = STD(C_stg,ch[:, 4]) /* STD():Standard deviation of scenarios in the bucket */
    end
    return (B_stg,ch,p, μ(B_stg,ch,p), σ(B_stg,ch,p))
```

short notice, are almost costless. In case 2, which is shown in Figure 4.12b, it is assumed that a change in g_2 is costly on very short notice, i.e. just before delivery time, but not costly in the intraday markets. Hence, the relevant cost parameters are $\Delta a^{ID_k^{buy}} = \Delta a^{ID_k^{sell}} = 0, k = 1, 2, 3$, $\Delta a^{RT^{up}} = \Delta a^{RT^{dn}} = 5$ and $b^{DA} = b^{ID_k^{buy}} = b^{ID_k^{sell}} = b^{RT^{up}} = b^{RT^{dn}} = 0, k = 1, 2, 3$.

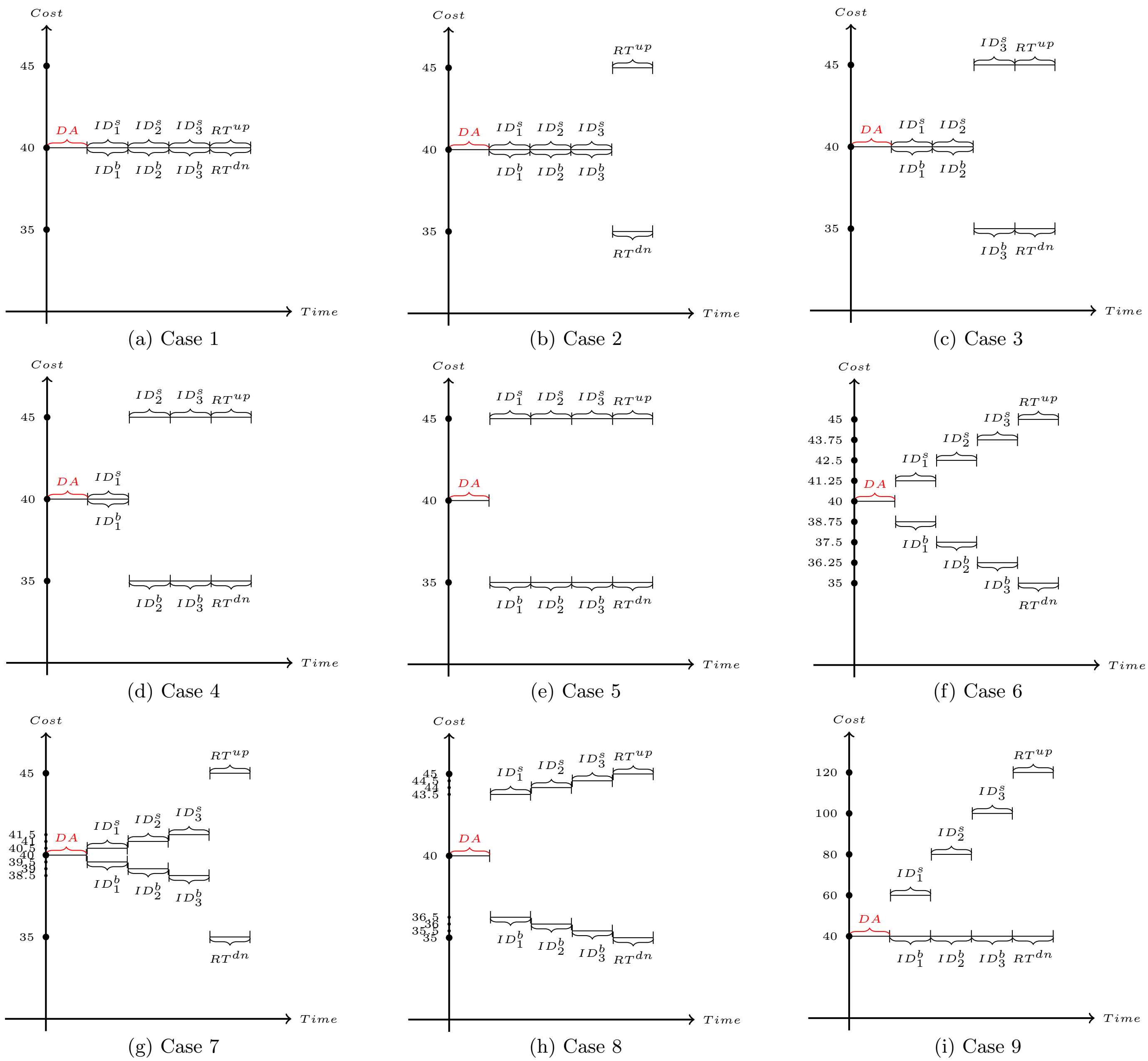
Similar interpretations can be made for the other cases. Thus, the cases differ with respect to how the generation cost develops over time, from the day-ahead market until real-time. In order to focus on the effect of cost changes and their timing, the five first cases have cost either equal to the day-ahead cost or 5 $\$/MWh$ higher/lower. In case 6, we consider linearly increasing/decreasing flexibility cost, while cases 7 and 8, respectively, model convex and concave cost functions for sell and up-regulation and concave and convex cost functions for buy and down-regulation. In contrast to all cases 1 to 8, where cost functions are symmetric, in case 9, g_2 will buy back or down-regulate with the same cost as in the day-ahead market, while it will sell or up-regulate with a linearly increasing cost function. So, in case 9 the flexibility costs are asymmetric.

4.6.1 Numerical results for the asymmetric scenario tree in Figure 4.8

The detailed results for the asymmetric scenario tree in Figure 4.8, and with cost parameters equal to case 5, is presented in Table B1 in the Appendix B. For each scenario, the following quantities are displayed for intraday placements ID_1, ID_2, ID_3, as well as $No\ ID$: sell/buy quantities (positive values for sell and negative values for buy) and relevant cost (negative numbers are income) in intraday, up/down regulation quantities and associated cost/income in real-time, the net change in cost due to intraday and real-time, and the total cost of generation and re-adjustments in all markets, i.e. day-ahead, intraday and real-time. The last column displays the sum of absolute values of quantity adjustments in intraday and real-time markets.

From Table B1 in Appendix B, we highlight the following observations:

1. From the quantity rows we notice that for all scenarios the total adjustment in intraday and real-time quantities (when there is an intraday market) is equal to the adjustment in real-time quantity when $'No\ ID'$ is considered. For instance, in scenario 2 the total quantity adjustment in both intraday and real-time ($ID_1 + RT = 550 + 550$, $ID_2 + RT = 1000 + 100$, $ID_3 + RT = 1350 - 250$) is equal to 1100 ($RT + No\ ID = 1100$). The reason is that demand is inelastic and there is no need for load-shedding in this case.
2. Even if the total quantity adjustments are the same within each scenario, the adjustments in each sequential step vary a lot, depending on where the intraday market is placed. This can be seen from the last column in Table B1, showing the sum of absolute values of quantity adjustments for each scenario and each intraday market placement. Since we assume that the wind power generator bids according to expected wind power at delivery time in each market, and this conditional expectation changes through the scenario tree, there may be both positive and negative sequential adjustments in a given scenario (see for instance scenario 4). In case 5, both are costly.
3. If the intraday and real-time quantities adjust in the same direction (i.e. sell in ID and up-regulate in RT or buy in ID and down-regulate in RT) then the 'net change in cost' and 'final cost' are equivalent to the corresponding costs for $RT + No\ ID$. However, if adjustments are in opposite directions (i.e. buy in ID and up-regulate in RT or sell in ID and down-regulate in RT) then the 'net change in cost' and 'final cost' are higher than the corresponding $RT + No\ ID$ cost. For instance, in scenario 2:
$ID_1 : 550 \cdot 45 + 550 \cdot 45 = 49500$



(a) Case 1 (b) Case 2 (c) Case 3
(d) Case 4 (e) Case 5 (f) Case 6
(g) Case 7 (h) Case 8 (i) Case 9

Figure 4.12. Assumptions on flexibility cost of g_2

$ID_2 : 1000 \cdot 45 + 100 \cdot 45 = 49500$

$ID_3 : 1350 \cdot 45 + (-250) \cdot 35 = 52000$

$No\ ID : 1100 \cdot 45 = 49500$

The first point is valid for all considered cost parameter cases. The consequences of the second and third points are contingent on the flexibility cost parameters, and may result in different final cost rankings of possible intraday placements for the cases considered.

We rank the best intraday placements based on expected total cost of generation. The expected total cost of generation for all 16 scenarios for all cost parameter cases 1 to 9 are summarized in Table 4.2. There is one row for each intraday market placement, as well as not having an intraday market at all. The last row shows the Expected Value with Perfect Information (EVPI), i.e. each scenario cleared in an optimal dispatch with day-ahead cost parameters.

Table 4.2. Expected total cost for different cost parameters and intraday placements for the asymmetric scenario tree

	Case 1	Case 2	Case 3	Case 4	Case 5	Case 6	Case 7	Case 8	Case 9
ID_1	222000	224625	224625	224625	227375	225313	224900	226550	248500
ID_2	222000	223750	223750	226500	226500	225125	224300	225950	247000
ID_3	222000	223250	226625	226625	226625	225781	224263	226288	252250
No ID	222000	225375	225375	225375	225375	225375	225375	225375	249000
EVPI	222000	222000	222000	222000	222000	222000	222000	222000	222000

Case 1

In case 1, deviating from the day-ahead plan does not cost anything, and even though uncertainty is decreasing from day-ahead to real-time (and therefore from ID_1 to ID_3), it doesn't matter if or where the intraday market is added, the cost are the same no matter, and equal to the EVPI. This case can illustrate a power system with fully flexible resources, for instance one dominated by hydropower with large reservoirs. Hence, with costless flexibility, adding intraday auctions does not have any impact on the final total cost of the system, and real-time markets would be sufficient to obtain efficiency in generation.

Case 2, 3 and 4

In case 2, there is a sharp increase in cost when g_2 quantities are adjusted in real time rather than intraday. In cases 3 and 4, the cost increase occurs earlier. In these cases, we can clearly see the trade-off, where the uncertainty factor tends to favour a later timing of the auction, while increasing flexibility cost favours an early one. In case 2, participation in any of the intraday markets does not incur extra cost, hence g_2 waits until more information is available and until the cost increase becomes too large, ID_3 being the best placement with lowest expected total cost. In cases 3 and 4, the best intraday timings are ID_2 and ID_1, respectively.

Case 5

In case 5, quantity adjustments are equally costly (compared to the day-ahead cost parameters) in all possible intraday markets, as well as the real-time market. Thus, it is not surprising that we prefer to wait as long as possible until all uncertainty is resolved, and the best decision is to have no intraday market and resolve necessary quantity adjustments in the real-time market. In this respect, this case is similar to case 1, showing that if intraday flexibility costs are equal either to day-ahead or real-time costs, then it leads us to the "no intraday market" decision.

Considering only the potential intraday market placements, since adjustment costs are constant, and since uncertainty (measured by standard deviation) is reduced over time in the scenario tree, we would expect ID_3 to be the better choice for an intraday auction, if we were to have one. This is however, and somewhat surprisingly, not the case. Part of the reason for this follows from our assumption that in each market stage, the wind power producer adjusts its position to the updated conditional expected wind power available in real-time. To understand why, we consider more carefully the expected total cost, which in our numerical example, with inelastic demand and $b_i = 0$, can be written as follows:

$$\mathop{\mathbb{E}}_{\omega^{ID},\omega^{RT}} \left[\sum_i \left(a_i^{DA} x_i^{DA} + a_i^{sell} x_{i,\omega^{ID}}^{sell} - a_i^{buy} x_{i,\omega^{ID}}^{buy} + a_i^{up} x_{i,\omega^{RT}}^{up} - a_i^{dn} x_{i,\omega^{RT}}^{dn} \right) \right] \tag{4.19}$$

Since g_2 is the only flexible resource in the system, that can participate in intraday and real-time markets, the expression in 4.19 can be written as follows:

$$\sum_i a_i^{DA} x_i^{DA} + a_{g_2}^{sell} \mathop{\mathbb{E}}_{\omega^{ID}} (x_{g_2,\omega^{ID}}^{sell}) - a_{g_2}^{buy} \mathop{\mathbb{E}}_{\omega^{ID}} (x_{g_2,\omega^{ID}}^{buy}) + a_{g_2}^{up} \mathop{\mathbb{E}}_{\omega^{RT}} (x_{g_2,\omega^{RT}}^{up}) - a_{g_2}^{dn} \mathop{\mathbb{E}}_{\omega^{RT}} (x_{g_2,\omega^{RT}}^{dn}) \tag{4.20}$$

Table 4.3. Expected adjustment quantities in intraday and real time for the asymmetric scenario tree

	$\mathbb{E}(x^{sell})$	$\mathbb{E}(x^{buy})$	$\mathbb{E}(x^{up})$	$\mathbb{E}(x^{dn})$
ID_1	275	275	262.5	262.5
ID_2	275	275	175	175
ID_3	337.5	337.5	125	125
No ID	–	–	337.5	337.5

By neglecting the first term, which is connected to the day-ahead market and is common for all intraday placements, and just evaluating the expected cost of adjustments in 4.20, using the adjustment values from Table 4.3, the following values are obtained:

$ID_1 : 45 \cdot 275 \ - 35 \cdot 275 + 45 \cdot 262.5 \ - 35 \cdot 262.5 \ = 2750 + 2625 = 5375$

$ID_2 : 45 \cdot 275 \ - 35 \cdot 275 + 45 \cdot 175 \ - 35 \cdot 175 \ = 2750 + 1750 = 4500$

$ID_3 : 45 \cdot 337.5 - 35 \cdot 337.5 + 45 \cdot 125 - 35 \cdot 125 = 3375 + 1250 = 4625$

$No\ ID : 45 \cdot 337.5 - 35 \cdot 337.5 = 3375$

The values shown in Table 4.2 for case 5 are the sums of the numbers calculated above and the day-ahead cost, which is equal to 222000. Thus, we can see that the ranking of the intraday placements is the same as the ranking of adjustment cost, from the lowest to the highest, i.e. No ID $< ID_2 < ID_3 < ID_1$. This means that even if the standard deviation is reduced from ID_2 to ID_3, when generation positions are consistently adjusted in the markets to updated information about conditional expectations of wind availability, then the up- and down-adjustments are larger and therefore more costly in ID_3 than in ID_2. This shows that the trade-off between uncertainty and flexibility cost can be more complicated than expected, and moreover, depends on which strategy we assume for how market agents trade in the intraday markets.

Case 6

In this case there is a gradual (linear) increase in the flexibility costs, from day-ahead, through the different ID placements, and until real time. The trade-off between uncertainty and flexibility cost shows that ID_2 is the best intraday timing in this case. As Table 4.3 illustrates, because energy balance is enforced in every market clearing, expected sell and buy quantities are equal, and the same goes for expected up- and down-regulations. Hence, the expression in 4.20 can always be written as:

$$(a_{g_2}^{sell} - a_{g_2}^{buy}) \mathop{\mathbb{E}}_{\omega^{ID}}(x_{g_2,\omega^{ID}}^{sell/buy}) + (a_{g_2}^{up} - a_{g_2}^{dn}) \mathop{\mathbb{E}}_{\omega^{RT}}(x_{g_2,\omega^{RT}}^{up/dn}) \tag{4.21}$$

$ID_1 : 2.5 \cdot 275 + 10 \cdot 262.5 = 2750 + 2625 = 3312.5$

$ID_2 : 5 \cdot 275 + 10 \cdot 175 = 3125$

$ID_3 : 7.5 \cdot 337.5 + 10 \cdot 125 = 3781.25$

$No\ ID : 10 \cdot 337.5 = 3375$

Hence, the ranking of intraday placements from low to high cost, is as follows: $ID_2 < ID_1 < No\ ID < ID_3$.

Case 7 and 8

In cases 7 and 8, the increases in flexibility cost vary over time, in the sense that in case 7, there is a large cost increase late ("convex cost"), while in case 8, a jump in the flexibility cost comes early ("concave cost"). The result is that the best timing of an intraday auction is early (ID_2) in case 7 and late (i.e. $No\ ID$) in case 8.

Case 9

This case has asymmetric sell/buy and up/down flexibility costs. More specifically, there is no flexibility cost for reducing net injections. In this case, the trade-off places the intraday market in 2, i.e. ID_2.

4.6.2 Numerical results for the symmetric scenario tree in Figure 4.7

Table 4.4. Expected adjustment quantities in intraday and real time for the symmetric scenario tree

	$\mathbb{E}(x^{sell})$	$\mathbb{E}(x^{buy})$	$\mathbb{E}(x^{up})$	$\mathbb{E}(x^{dn})$
ID_1	250	250	375	375
ID_2	250	250	250	250
ID_3	375	375	250	250
No ID	–	–	375	375

Table 4.5. Expected total cost for different cases in the symmetric scenario tree

	Case 1	Case 2	Case 3	Case 4	Case 5	Case 6	Case 7	Case 8	Case 9
ID_1	214000	217750	217750	217750	220250	218375	218000	219500	249000
ID_2	214000	216500	216500	219000	219000	217750	217000	218500	244000
ID_3	214000	216500	220250	220250	220250	219312	217625	219875	256500
No ID	214000	217750	217750	217750	217750	217750	217750	217750	244000
EVPI	214000	214000	214000	214000	214000	214000	214000	214000	214000

Case 2

In this case all intraday placements have the same flexibility costs, while adjustments in real time are considerably more costly. Again we would expect ID_3 to be the better placement of an intraday auction, however ID_2 also shows the same expected adjustment cost. This can be explained by using Equation 4.21 together with the adjustment quantities in Table 4.4 to obtain expected adjustment costs as follows:

$ID_1 : 0 \cdot 250 \ + 10 \cdot 375 = 3750$

$ID_2 : 0 \cdot 250 \ + 10 \cdot 250 = 2500$

$ID_3 : 0 \cdot 375 + 10 \cdot 250 = 2500$

$No\ ID : 10 \cdot 375 = 3750$

Since intraday sell and buy flexibility costs are equal, their difference is zero. Hence, intraday adjustment costs do not matter, and only real time adjustments are important in this case. Since real time adjustments are equal for ID_2 and ID_3, as well as for ID_1 and $No\ ID$, ID_2 and ID_3 are equally good placements, and the same goes for ID_1 and $No\ ID$.

Other cases

As can be seen from Table 4.5, different cost parameters result in different best placements for an intraday auction, and the same kind of reasoning as in Section 4.6.1 can be utilized here.

4.6.3 Numerical results for the data-driven scenario tree described in Section 4.5.2

Table 4.6. Expected adjustment quantities in intraday and real time for the data-driven scenario tree

	$\mathbb{E}(x^{sell})$	$\mathbb{E}(x^{buy})$	$\mathbb{E}(x^{up})$	$\mathbb{E}(x^{dn})$
ID_1	34	34	124	124
ID_2	61	61	115	115
ID_3	87	87	97	97
No ID	–	–	126	126

Table 4.7. Expected total cost for different cases in the data-driven scenario tree

	Case 1	Case 2	Case 3	Case 4	Case 5	Case 6	Case 7	Case 8	Case 9
ID_1	161494	162732	162732	162732	163072	162817	162766	162970	172080
ID_2	161494	162645	162645	163258	163258	162952	162768	163135	173154
ID_3	161494	162465	163336	163336	163336	163118	162726	163249	174486
No ID	161494	162758	162758	162758	162758	162758	162758	162758	171606
EVPI	161494	161494	161494	161494	161494	161494	161494	161494	161494

For this scenario tree the most interesting cases are 2, 5 and 6, and these cases will be described further in the following. Cases 7, 8 and 9 are comparable to cases 2, 5 and 6, respectively.

Case 2

Even if the order of best intraday placements follow the pattern of reduced uncertainty, the following calculations can help to explain the decreasing expected total cost from ID_1 to ID_3:

$ID_1 : 0 \cdot 34 + 10 \cdot 124 = 1240$

$ID_2 : 0 \cdot 61 + 10 \cdot 115 = 1150$
$ID_3 : 0 \cdot 87 + 10 \cdot 97 = 970$
$No\ ID : 10 \cdot 126 = 1260$

Since the sell and buy costs are equal for all intraday placements, the intraday quantities do not play any role in deciding the best intraday placement. Only the decreasing trend of expected adjustment quantities in real time matters, and ID_3 is best.

Case 5

As for case 2, the uncertainty is reduced from ID_1 to ID_3, and flexibility costs are equal across all intraday placements. However, in contrast to case 2, in this case, the expected total cost increases from ID_1 to ID_3, and this can be explained by the following calculations:
$ID_1 : 10 \cdot 34 + 10 \cdot 124 = 1580$
$ID_2 : 10 \cdot 61 + 10 \cdot 115 = 1760$
$ID_3 : 10 \cdot 87 + 10 \cdot 97 = 1840$
$No\ ID : 10 \cdot 126 = 1260$

I.e. the best intraday placement is reversed compared to case 5, due to the cost difference between intraday buy and sell, and $No\ ID$ is the best option.

Case 6

In this case, flexibility costs increase linearly over time, while uncertainty is reduced. One could expect that this would favour the intermediate placement of an intraday market, i.e. ID_2, however, this is not the case:
$ID_1 : 2.5 \cdot 34 + 10 \cdot 124 = 1325$
$ID_2 : 5 \cdot 61 + 10 \cdot 115 = 1455$
$ID_3 : 7.5 \cdot 87 + 10 \cdot 97 = 1623$
$No\ ID : 10 \cdot 126 = 1260$

If an intraday market is to be added, ID_1 is the least cost option.

4.7 Conclusion

The increasing share of uncertain generation mostly coming from wind and solar makes European commission regulators to revise electricity market design and particularly pay more attention to intraday market. Regarding to the challenges that continuous trading intraday market faces with respect to the congestion management, adding one or more intraday auctions is on the agenda to facilitate trading in the short-term and create better transparency by delivering one price (instead of many prices in continuous trading) and provide a quicker and easier way to submit orders. If the decision is to add one auction between day-ahead and real-time when would be the best time to do that?

In this paper, we demonstrate that timing of intraday auction is affected by two opposing factors: uncertainty and flexibility cost. The earlier auctions confronted with the higher uncertainty but lower flexibility costs, while the later ones tackle with higher flexibility costs but lower uncertainty. By testing several scenario trees with uncertainty reduction characteristic from day-ahead to real-time, a tight trade-off between these two factors has been observed. Our findings reveal that even though standard deviation reduction is an important measure for uncertainty its reduction is not enough to say that always the latest intraday is the best by assuming the other variables as fixed. Therefore, the std reduction is mainly reflected in re-adjustment quantities, this means that the more std is reducing from day-ahead to real-time, the more re-adjustments are required. This is the reason that in some cases especially case 2 and 5, instead of observing ID_3 as the lowest expected total cost, the other intraday placements look less costly. Hence, it can be concluded that in the sequential market setting that expected wind power is utilized for clearing stochastic generators, the multiplicative effect of flexibility cost and re-adjustment quantities determine the best intraday place not just the trade off between flexibility cost and std reduction.

Experiments on diverse flexibility costs disclose very interesting results. For instance, in hydro-dominated systems where flexibility cost is very low, adding an intraday auction cannot be cost-effective while intraday auction can have a huge cost reduction for systems with very high flexibility costs, then the trade-off between uncertainty and flexibility is more evident.

In the simulated symmetric and asymmetric scenario trees, std is high at the begining (compared to data-driven scenario tree), illustrates an inaccurate 24-hour ahead forecast, while in the shorter-term forecasts 18, 12 and 6 hour ahead stds show a huge decrease, meaning that by getting closer to the delivery time, the forecasts getting much more accurate. Results show that in scenario trees with huge changes of std from day-ahead to real-time, which can be connected to the accuracy of forecasts, adding an intraday auction helps to relieve the total cost of the system, while in trees with not so conspicuous reduction in std, like data-driven scenario tree, our findings report that adding an intraday auction cannot relieve costs of the system.

However, in the future research the last finding require to be tested with more shorter-term forecasts. Because just having access to 24-hour ahead data leads us to not have intraday auction for most flexibility cost cases. Hence, having access to 24, 18, 12 and 6 hour ahead forecast data can reveal more trade-off between uncertainty and flexibility cost. We have also neglected congestion management in this paper. Therefore, the next natural step in future research is to see how the intraday placement will be affected by modeling congestion. Finally, it would be more interesting to model hybrid intraday market, a combination of continuous trading and an auction to see how the behavior of market participants will change and whether the main aim of auction, which is helping continuous trading in managing congestion, is achieved or not.

Appendix A. Proof of (4.13)

In order to prove the equality given by (4.13), four different combinations of intraday and real-time dispatch must be considered for any generator $i \in G^{ID}_{flex} \cap G^{RT}_{flex}$:

1. Sell $x_i^{ID^{sell}}$ in intraday and up-regulate $x_i^{RT^{up}}$ in real-time.
2. Buy back $x_i^{ID^{buy}}$ in intraday and down-regulate $x_i^{RT^{dn}}$ in real-time.
3. Buy back $x_i^{ID^{buy}}$ in intraday and up-regulate $x_i^{RT^{up}}$ in real-time.
4. Sell $x_i^{ID^{sell}}$ in intraday and down-regulate $x_i^{RT^{dn}}$ in real-time.

Similar cases can be defined for flexible consumers, but since the analysis is similar to the one presented for generators, further discussions of consumer cases are avoided.

Case 1: Sell-Up

Since $x_i^{ID^{buy}} = x_i^{RT^{dn}} = 0$, Equations (4.10), (4.11), and (4.12) can be written as:

$$a_i^{DA}(x_i^{DA} + x_{i,\omega^{ID}}^{ID^{sell}} + x_{i,\omega^{RT}}^{RT^{up}}) + \frac{1}{2}b_i^{DA}(x_i^{DA} + x_{i,\omega^{ID}}^{ID^{sell}} + x_{i,\omega^{RT}}^{RT^{up}})^2 \tag{A1}$$

$$(a_i^{ID^{sell}} - a_i^{DA})(x_{i,\omega^{ID}}^{ID^{sell}} + x_{i,\omega^{RT^{up}}}^{RT^{up}}) + \frac{1}{2}(b_i^{ID^{sell}} - b_i^{DA})(x_{i,\omega^{ID}}^{ID^{sell}} + x_{i,\omega^{RT}}^{RT^{up}})^2 \tag{A2}$$

$$(a_i^{RT^{up}} - a_i^{ID^{sell}})(x_{i,\omega^{RT}}^{RT^{up}}) + \frac{1}{2}(b_i^{RT^{up}} - b_i^{ID^{sell}})(x_{i,\omega^{RT}}^{RT^{up}})^2 \tag{A3}$$

By summing these equations and cancelling equal terms as illustrated in Table A1, we get

$$\begin{aligned} a_i^{DA}x_i^{DA} + a_i^{ID^{sell}}x_{i,\omega^{ID}}^{ID^{sell}} + a_i^{RT^{up}}x_{i,\omega^{RT}}^{RT^{up}} + \frac{1}{2}(b_i^{ID^{sell}} - b_i^{DA})\ x_{i,\omega^{ID}}^{ID^{sell}2} + \frac{1}{2}(b_i^{RT^{up}} - b_i^{DA})\ x_{i,\omega^{RT}}^{RT^{up}2} \\ +(b_i^{ID^{sell}} - b_i^{DA})\ x_{i,\omega^{ID}}^{ID^{sell}}\ x_{i,\omega^{RT}}^{RT^{up}} + \frac{1}{2}b_i^{DA}(x_i^{DA} + x_{i,\omega^{ID}}^{ID^{sell}} + x_{i,\omega^{RT}}^{RT^{up}})^2, \end{aligned} \tag{A4}$$

which is equal to (4.13) for this case.

Table A1. Simplifying (A1), (A2), and (A3).

x^{DA}	$x^{ID^{sell}}$	$x^{RT^{up}}$	x^{DA^2}	$x^{ID^{sell2}}$	$x^{RT^{up2}}$	$2x^{DA}x^{ID^{sell}}$	$2x^{DA}x^{RT^{up}}$	$2x^{ID^{sell}}x^{RT^{up}}$
a^{DA}	$\cancel{a^{DA}}$	$\cancel{a^{DA}}$	0	$b^{ID^{sell}} - b^{DA}$	$\cancel{b^{ID^{sell}}} - b^{DA}$	0	0	$b^{ID^{sell}} - b^{DA}$
0	$a^{ID^{sell}} - \cancel{a^{DA}}$	$\cancel{a^{ID^{sell}}} - \cancel{a^{DA}}$	0	0	$b^{RT^{up}} - \cancel{b^{ID^{sell}}}$	0	0	0
0	0	$a^{RT^{up}} - \cancel{a^{ID^{sell}}}$	0	0	0	0	0	0

Case 2: Buy-Down

Since $x_i^{ID^{sell}} = x_i^{RT^{up}} = 0$, Equations (4.10), (4.11), and (4.12) can be written as:

$$a_i^{DA}(x_i^{DA} - x_{i,\omega^{ID}}^{ID^{buy}} - x_{i,\omega^{RT}}^{RT^{dn}}) + \frac{1}{2}b_i^{DA}(x_i^{DA} - x_{i,\omega^{ID}}^{ID^{buy}} - x_{i,\omega^{RT}}^{RT^{dn}})^2 \tag{A5}$$

$$(a_i^{DA} - a_i^{ID^{buy}})(x_{i,\omega^{ID}}^{ID^{buy}} + x_{i,\omega^{RT^{dn}}}^{RT^{dn}}) + \frac{1}{2}(b_i^{ID^{buy}} - b_i^{DA})(x_{i,\omega^{ID}}^{ID^{buy}} + x_{i,\omega^{RT}}^{RT^{dn}})^2 \tag{A6}$$

$$(a_i^{ID^{buy}} - a_i^{RT^{dn}})\ x_{i,\omega^{RT}}^{RT^{dn}} + \frac{1}{2}(b_i^{RT^{dn}} - b_i^{ID^{buy}})\ x_{i,\omega^{RT}}^{RT^{dn}2} \tag{A7}$$

By summing and cancelling out equal terms we get

$$\begin{aligned}a_i^{DA}x_i^{DA} - a_i^{ID^{buy}}x_{i,\omega^{ID}}^{ID^{buy}} - a_i^{RT^{dn}}x_{i,\omega^{RT}}^{RT^{dn}} + \frac{1}{2}(b_i^{ID^{buy}} - b_i^{DA})\ x_{i,\omega^{ID}}^{ID^{buy}2} + \frac{1}{2}(b_i^{RT^{dn}} - b_i^{DA})\ x_{i,\omega^{RT}}^{RT^{dn}2} \\ +(b_i^{ID^{buy}} - b_i^{DA})\ x_{i,\omega^{ID}}^{ID^{buy}}\ x_{i,\omega^{RT}}^{RT^{dn}} + \frac{1}{2}b_i^{DA}(x_i^{DA} - x_{i,\omega^{ID}}^{ID^{buy}} - x_{i,\omega^{RT}}^{RT^{dn}})^2\end{aligned} \tag{A8}$$

which equals (4.13) for this case.

Case 3: Buy-Up

Since $x_i^{ID^{sell}} = x_i^{RT^{dn}} = 0$, Equations (4.10), (4.11), and (4.12) can be written as:

$$a_i^{DA}(x_i^{DA} - x_{i,\omega^{ID}}^{ID^{buy}} + x_{i,\omega^{RT}}^{RT^{up}}) + \frac{1}{2}b_i^{DA}(x_i^{DA} - x_{i,\omega^{ID}}^{ID^{buy}} + x_{i,\omega^{RT}}^{RT^{up}})^2 \tag{A9}$$

$$(a_i^{DA} - a_i^{ID^{buy}})(x_{i,\omega^{ID}}^{ID^{buy}} - x_{i,\omega^{RT^{up}}}^{RT^{up}}) + \frac{1}{2}(b_i^{ID^{buy}} - b_i^{DA})(x_{i,\omega^{ID}}^{ID^{buy}} - x_{i,\omega^{RT}}^{RT^{up}})^2 \tag{A10}$$

$$(a_i^{RT^{up}} - a_i^{ID^{buy}})\ x_{i,\omega^{RT}}^{RT^{up}} + \frac{1}{2}(b_i^{RT^{up}} - b_i^{ID^{buy}})\ x_{i,\omega^{RT}}^{RT^{up}2} \tag{A11}$$

Summing and cancelling out equal terms gives us

$$\begin{aligned}a_i^{DA}x_i^{DA} - a_i^{ID^{buy}}x_{i,\omega^{ID}}^{ID^{buy}} + a_i^{RT^{up}}x_{i,\omega^{RT}}^{RT^{up}} + \frac{1}{2}(b_i^{ID^{buy}} - b_i^{DA})\ x_{i,\omega^{ID}}^{ID^{buy}2} + \frac{1}{2}(b_i^{RT^{up}} - b_i^{DA})\ x_{i,\omega^{RT}}^{RT^{up}2} \\ -(b_i^{ID^{buy}} - b_i^{DA})\ x_{i,\omega^{ID}}^{ID^{buy}}\ x_{i,\omega^{RT}}^{RT^{up}} + \frac{1}{2}b_i^{DA}(x_i^{DA} - x_{i,\omega^{ID}}^{ID^{buy}} + x_{i,\omega^{RT}}^{RT^{up}})^2,\end{aligned} \tag{A12}$$

which equals (4.13) for this case.

Case 4: Sell-Down

Since $x_i^{ID^{buy}} = x_i^{RT^{up}} = 0$, Equations (4.10), (4.11), and (4.12) can be written as:

$$a_i^{DA}(x_i^{DA} + x_{i,\omega^{ID}}^{ID^{sell}} - x_{i,\omega^{RT}}^{RT^{dn}}) + \frac{1}{2}b_i^{DA}(x_i^{DA} + x_{i,\omega^{ID}}^{ID^{sell}} - x_{i,\omega^{RT}}^{RT^{dn}})^2 \tag{A13}$$

$$(a_i^{ID^{sell}} - a_i^{DA})(x_{i,\omega^{ID}}^{ID^{sell}} - x_{i,\omega^{RT}}^{RT^{dn}}) + \frac{1}{2}(b_i^{ID^{sell}} - b_i^{DA})(x_{i,\omega^{ID}}^{ID^{sell}} - x_{i,\omega^{RT}}^{RT^{dn}})^2 \tag{A14}$$

$$(a_i^{ID^{sell}} - a_i^{RT^{dn}})\ x_{i,\omega^{RT}}^{RT^{dn}} + \frac{1}{2}(b_i^{RT^{dn}} - b_i^{ID^{sell}})\ x_{i,\omega^{RT}}^{RT^{dn}2} \tag{A15}$$

Summing and cancelling out equal terms gives us

$$a_i^{DA} x_i^{DA} + a_i^{ID^{sell}} x_{i,\omega^{ID}}^{ID^{sell}} - a_i^{RT^{dn}} x_{i,\omega^{RT}}^{RT^{dn}} + \frac{1}{2}(b_i^{ID^{sell}} - b_i^{DA})\ x_{i,\omega^{ID}}^{ID^{sell}2} + \frac{1}{2}(b_i^{RT^{dn}} - b_i^{DA})\ x_{i,\omega^{RT}}^{RT^{dn}2}$$
$$-(b_i^{ID^{sell}} - b_i^{DA})\ x_{i,\omega^{ID}}^{ID^{sell}}\ x_{i,\omega^{RT}}^{RT^{dn}} + \frac{1}{2} b_i^{DA} (x_i^{DA} + x_{i,\omega^{ID}}^{ID^{sell}} - x_{i,\omega^{RT}}^{RT^{dn}})^2, \tag{A16}$$

which equals (4.13) for this case.

Appendix B

Table B1. Detailed results for the asymmetric scenario tree with cost parameters of case 5

Scenario	Description	ID1	ID2	ID3	RT	Net Cost Change	Final Cost	Absolute Quantity
1	ID1 quantity	550			1050			1600
	ID1 cost	24750			47250	72000	294000	
	ID2 quantity		1000		600			1600
	ID2 cost		45000		27000	72000	294000	
	ID3 quantity			1350	250			1600
	ID3 cost			60750	11250	72000	294000	
	No ID quantity				1600			
	No ID cost				72000	72000	294000	
2	ID1 quantity	550			550			1100
	ID1 cost	24750			24750	49500	271500	
	ID2 quantity		1000		100			1100
	ID2 cost		45000		4500	49500	271500	
	ID3 quantity			1350	-250			1600
	ID3 cost			60750	-8750	52000	274000	
	No ID quantity				1100			
	No ID cost				49500	49500	271500	
3	ID1 quantity	550			350			900
	ID1 cost	24750			15750	40500	262500	
	ID2 quantity		1000		-100			1100
	ID2 cost		45000		-3500	41500	263500	
	ID3 quantity			650	250			900
	ID3 cost			29250	11250	40500	262500	
	No ID quantity				900			
	No ID cost				40500	40500	262500	
4	ID1 quantity	550			-150			700
	ID1 cost	24750			-5250	19500	241500	
	ID2 quantity		1000		-600			1600
	ID2 cost		45000		-21000	24000	246000	
	ID3 quantity			650	-250			900
	ID3 cost			29250	-8750	20500	242500	
	No ID quantity				400			
	No ID cost				18000	18000	240000	
5	ID1 quantity	550			150			700
	ID1 cost	24750			6750	31500	253500	
	ID2 quantity		100		600			700
	ID2 cost		4500		27000	31500	253500	
	ID3 quantity			450	250			700
	ID3 cost			20250	11250	31500	253500	
	No ID quantity				700			
	No ID cost				31500	31500	253500	
6	ID1 quantity	550			-350			900
	ID1 cost	24750			-12250	12500	234500	
	ID2 quantity		100		100			200
	ID2 cost		4500		4500	9000	231000	
	ID3 quantity			450	-250			700
	ID3 cost			20250	-8750	11500	233500	
	No ID quantity				200			
	No ID cost				9000	9000	231000	

Scenario	Description	ID1	ID2	ID3	RT	Net Cost Change	Final Cost	Absolute Quantity
7	ID1 quantity	550			-550			1100
	ID1 cost	24750			-19250	5500	227500	
	ID2 quantity		100		-100			200
	ID2 cost		4500		-3500	1000	223000	
	ID3 quantity			-250	250			500
	ID3 cost			-8750	11250	2500	224500	
	No ID quantity							
	No ID cost						222000	
8	ID1 quantity	550			-1050			1600
	ID1 cost	24750			-36750	-12000	210000	
	ID2 quantity		100		-600			700
	ID2 cost		4500		-21000	-16500	205500	
	ID3 quantity			-250	-250			500
	ID3 cost			-8750	-8750	-17500	204500	
	No ID quantity				-500			
	No ID cost				-17500	-17500	204500	
9	ID1 quantity	-550			1050			1600
	ID1 cost	-19250			47250	28000	250000	
	ID2 quantity		-100		600			700
	ID2 cost		-3500		27000	23500	245500	
	ID3 quantity			250	250			500
	ID3 cost			11250	11250	22500	244500	
	No ID quantity				500			
	No ID cost				22500	22500	244500	
10	ID1 quantity	-550			550			1100
	ID1 cost	-19250			24750	5500	227500	
	ID2 quantity		-100		100			200
	ID2 cost		-3500		4500	1000	223000	
	ID3 quantity			250	-250			500
	ID3 cost			11250	-8750	2500	224500	
	No ID quantity							
	No ID cost						222000	
11	ID1 quantity	-550			350			900
	ID1 cost	-19250			15750	-3500	218500	
	ID2 quantity		-100		-100			200
	ID2 cost		-3500		-3500	-7000	215000	
	ID3 quantity			-450	250			700
	ID3 cost			-15750	11250	-4500	217500	
	No ID quantity				-200			
	No ID cost				-7000	-7000	215000	
12	ID1 quantity	-550			-150			700
	ID1 cost	-19250			-5250	-24500	197500	
	ID2 quantity		-100		-600			700
	ID2 cost		-3500		-21000	-24500	197500	
	ID3 quantity			-450	-250			700
	ID3 cost			-15750	-8750	-24500	197500	
	No ID quantity				-700			
	No ID cost				-24500	-24500	197500	

Scenario	Description	ID1	ID2	ID3	RT	Net Cost Change	Final Cost	Absolute Quantity
13	ID1 quantity	-550			150			700
	ID1 cost	-19250			6750	-12500	209500	
	ID2 quantity		-1000		600			1600
	ID2 cost		-35000		27000	-8000	214000	
	ID3 quantity			-650	250			900
	ID3 cost			-22750	11250	-11500	210500	
	No ID quantity				-400			
	No ID cost				-14000	-14000	208000	
14	ID1 quantity	-550			-350			900
	ID1 cost	-19250			-12250	-31500	190500	
	ID2 quantity		-1000		100			1100
	ID2 cost		-35000		4500	-30500	191500	
	ID3 quantity			-650	-250			900
	ID3 cost			-22750	-8750	-31500	190500	
	No ID quantity				-900			
	No ID cost				-31500	-31500	190500	
15	ID1 quantity	-550			-550			1100
	ID1 cost	-19250			-19250	-38500	183500	
	ID2 quantity		-1000		-100			1100
	ID2 cost		-35000		-3500	-38500	183500	
	ID3 quantity			-1350	250			1600
	ID3 cost			-47250	11250	-36000	186000	
	No ID quantity				-1100			
	No ID cost				-38500	-38500	183500	
16	ID1 quantity	-550			-1050			1600
	ID1 cost	-19250			-36750	-56000	166000	
	ID2 quantity		-1000		-600			1600
	ID2 cost		-35000		-21000	-56000	166000	
	ID3 quantity			-1350	-250			1600
	ID3 cost			-47250	-8750	-56000	166000	
	No ID quantity				-1600			
	No ID cost				-56000	-56000	166000	
Average of sum of absolute ID and RT quantities							ID1	1075
							ID2	900
							ID3	925
Sum of absolute ID and RT quantities							ID1	17200
							ID2	14400
							ID3	14800

Chapter 5

Simulation of Continuous Trading in an Intraday Electricity Market

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Abstract

The growing penetration of intermittent renewable energy sources has increased the importance of efficient intraday electricity markets, seeing that they provide an environment where market participants could correct their day-ahead decisions due to imbalances caused by intermittency or any other reasons. For more efficient utilization of generation resources across the whole continent, the European commission has established a target model to integrate all intraday markets based on continuous double auctions or limit order book. A fundamental model for a limit order book simulation is represented in this paper. Very simplifying assumptions are made on price and quantity decisions. Instead, more focus is on the limit order book modeling in which market participants (they can be any type of intermittent and conventional generators, elastic consumers and even financial traders) randomly (based on uniform distribution) submit market or limit orders with random quantities chosen from their residual capacity or cleared capacity (depending on ask or bid order submission) and their day-ahead marginal cost as the submitted price. The model is able to manage the order arrivals, their addition to the list (as limit order) or matching them with the best available opposite order (market order), store the matched trades, update the quantities of matched orders and finally accept part (or whole) of matched orders to maintain the feasibility of the transmission network with respect to the nodal constraints of the network.

Keywords: Market Microstructure, Continuous trading by limit order book, Simulation, Renewable integration

5.1 Introduction

Electricity markets are designed as double auctions wherein sellers and buyers are able to submit their offers. Double auctions are classified into two types, i.e. auction and continuous clearing. For example, all European day-ahead and some intraday markets are based on auction clearing in which trade determination and price setting rely on power exchanges. Hence, the power exchange determines which offers are successful and finds the clearing price of transactions. While in continuous double auctions (CDAs), trade determination and price setting is not generally built upon an institution, meaning that market participants themselves decide which quantities are traded at which price and the clearing process is delegated to market participants. Therefore, by providing an appropriate tool, a power exchange can give information to market participants and allow them to engage in transactions with each other. A *limit order book* can be such a tool. In a limit order book, market participants can submit a bid (request to buy) or ask (request to sell) to the orderbook by specifying a quantity and a price.

Market participants basically can submit two types of orders:

- Limit order : reflects the maximum willingness to pay (bid) or the minimum willingness to accept (ask) for each unit (megawatt hour) of the specified quantity. As Table 5.1 shows, bids and asks are sorted respectively in descending and ascending orders. These sortings place the current "best offers" at the top of the order book. The highest bid price in Table 5.1 is less than the lowest ask price, which implies that the buyer's willingness to pay is not high enough for the seller to trade. The magnitude of the difference between the prices at the top of the order book is called the bid-ask spread. A limit order can be matched either partly or entirely. If the limit order is not fully matched, it will remain active in the market until it is matched or cancelled. Some execution constraints on limit orders have been defined for continuous intraday electricity markets, for instance Fill or Kill (FOK) and Immediate or Cancel (IOC). With an FOK constraint, the entire volume of the order will either be matched immediately after submission or cancelled right away. With an IOC constraint, as much as possible of the order will be matched immediately after submission and the remaining quantity will be cancelled instantly.
- Market order : participants submit a market order when they buy or sell a certain quantity at the best available sell or buy price. Once a market order has arrived, it is matched instantly with the best available price in the order book and trade occurs.

Table 5.1. Limit order book example

Bid			Ask		
time	price	quantity	time	price	quantity
10:18	50	15	10:10	52	20
10:22	47	25	10:29	54	15
10:07	46	20	10:05	55	25
10:16	43	25	10:13	58	22

Limit orders remain in the order book until they are matched with a market order or cancelled.

As mentioned before, only a few European intraday markets such as the Iberaian (Spain and Portugal) and the Italian markets are discrete auctions. The Iberian market is divided into 7 auctions with different gate-closure and trading hours coverage. Pricing is based on the marginal pricing rule (Chaves-Ávila and Fernandes (2015)). Except for these two mentioned markets, almost all other European intraday markets are continuous double auctions. Elbas which is run by Nordpool spot AS is a good example of this type, and covers the Nordic and Baltic countries, Germany and the UK. Although Elbas covers many countries, the trading volume is relatively low. For instance, only 8.3 Twh was traded on Elbas in 2018, which was just 0.02% of the total volume traded in the Nordpool day-ahead market (Elspot). One possible reason for this low volume is that the installed capacity of intermittent renewables is not very high in the countries covered by Elbas. In 2017, the combined capacity of wind turbines and photovoltaic installations in Denmark, Finland, Norway, Sweden, Estonia, Latvia and Lithuania amounted to 17.2 GW. For comparison, the capacity in Germany was nearly 97.4 GW (WindEurope (2017)).

The growth of the intermittent generation capacity has increased the importance of efficient intraday markets, seeing that it becomes more challenging for market participants to be in balance after the closing of the day-ahead market. Hence, there will be an increasing interest in trading in the intraday markets. It is a potential benefit for both market participants and power systems that the network is in balance closer to the delivery time, in order to reduce the need for reserves and associated costs. The European commission has established a target model to integrate all intraday markets based on continuous trading. Therefore, the XBID project (cross-border intraday) was launched to create a joint integrated intraday cross-zonal market. As mentioned in the XBID documents (NordPool (2016a)) the main aims of integration are to promote effective competition and pricing, increase liquidity and enable a more efficient utilization of generation resources across Europe.

This measure illustrates the importance of intraday markets in integrating renewables and therefore more in-depth studies are required to analyze the best market design - auction, continuous or hybrid - and finds suitable congestion management technique for the intraday market. Simulation is one of the key tools to imitate the operation of continuous trading intraday market. Since none of the former electricity markets has been designed as a continuous trading market, this topic is new for many power market experts. Even though the experiences gained from the stock market, which uses the limit order book tool, can open new doors to electricity market experts, the specific characteristics of power markets, like physical transmission network constraints, power plant and consumer restrictions, etc. may limit the value of these experiences and call for specific adjustments.

The rest of the paper is organized as follows. A comprehensive intraday electricity market literature review is given in Section 5.2. In Section 5.3 the main reasons for participating in intraday markets will be discussed. The research assumptions, the mathematical formulation and simulation of limit orders, market orders, matching of orders, updating quantities for matched agents, etc., are represented in Section 5.4. Section 5.5 introduces an illustrative example and the results of the computational study. Corresponding insights and suggestions for future research are explained in section 5.6. Finally, Section 5.7 concludes the paper.

5.2 literature Review

The literature about intraday markets can be categorized into three main groups:

- Intraday prices
- Trading strategy of different types of market participants in the intraday market
- Modeling of intraday markets

Empirical or analytical analysis of intraday prices has evolved very rapidly over recent years. While Soysal et al. (2017), Sekamane (2018), Panagiotelis and Smith (2008), Gürtler and Paulsen (2018), Hagemann (2013b), Ziel (2017) and Karanfil and Li (2015) suggest time-series regression-based methods and Monteiro et al. (2016)

and Kolberg and Waage (2018) utilize several kind of neural networks and deep learning techniques for forecasting intraday prices, some other papers like Pape et al. (2016) and Kiesel and Paraschiv (2017) utilize the econometric approaches to extract the relation between day-ahead, intraday and sometimes balancing market prices.

In some other studies various optimization approaches have been utilized by different types of market participants so as to find their optimal bidding and trading strategies to operate in sequential markets. Löhndorf et al. (2013), Braun (2016), Braun and Hoffmann (2016), Engmark et al. (2018), Engmark et al. (2017) develop bidding strategies for hydropower or pumped storage technologies to optimize their dispatch in two-stage day-ahead and intraday markets, while Vardanyan and Hesamzadeh (2017) suggest optimal coordinated bidding of a risk-averse profit-maximizing hydropower producer in three-settlement day-ahead, intraday, and real-time markets. To the best of our knowledge, Boukas et al. (2018) is the only paper that utilizes markov decision processes and deep learning to find the optimal bidding strategy of a storage operator in a continuous trading intraday market. Since one of the main reasons of designing a continuous trading intraday market is to facilitate trades for wind and solar producers, many interesting studies have been done to suggest the optimal trading strategies for these intermittent technologies. While Du et al. (2018) and Usaola and Moreno (2009) focus on the co-optimization of a wind producer's trading strategies in both day-ahead and intraday markets, Skajaa et al. (2015) and Garnier and Madlener (2015) propose an efficient trading strategy to balance the forecast errors of wind producers in a continuous trading intraday market.

In most papers on electricity intraday market design, the continuous double auction structure of this market has not been paid much attention, and until recently, mathematical co-optimization of auction-based day-ahead and intraday markets (and sometimes balancing market) were the predominant approach. For example, Abrell and Kunz (2015) develop a rolling planning procedure in a stochastic electricity market setting to analyze the impact of both uncertain wind generation as well as network constraints on the results of sequential markets. By modeling the German power system, they illustrate how intermittent wind generation affects the flexibility providers' dispatch in an auction-based intraday market. More recents papers like Neuhoff et al. (2016a) and Neuhoff et al. (2016c) empirically assess the hybrid intraday market design, which is based on the simultaneous operation of continuous trading and several discrete auctions. In Neuhoff et al. (2016c) the effect of adding the 3 pm local auction (for quarters in Germany in December 2014 at the European Power Exchange (EPEX SPOT)) to the current continuous trading is investigated. They find that the additional auction enhances liquidity, and gives rise to higher market depth and reduced price volatility. Neuhoff et al. (2016a) analyze how the various intraday market designs - one or more auctions alongside or instead of continuous intraday trading - affect market efficiency. They conclude that the introduction of intraday auctions entails the potential to support efficiency.

As mentioned before in Section 5.1, the limit order book is the tool for continuous trading intraday market operations. The literature on limit order book modeling and trading strategies in stock market continuous double auctions is more abundant than continuous intraday markets for electricity. Von Selasinsky (2016) reviewed the related literature very comprehensively. Based on his classification, limit order books can be modeled either by equilibrium or by stochastic models. The former approach is used to illustrate how the interaction of market agents forms the prices, however the main disadvantage of this approach is that due to the anonymity of the agents, their characteristics are not known. Hence, the parameters of such models are unobservable and this gives incomplete intuition about the statistical properties of limit order books (Luckock et al., 2003). Stochastic modeling of order book dynamics, on the other hand, is based on the assumption that the evolution of the order book is driven by the collective behavior of all market participants not the individual ones. Therefore, most of the models in this category (in stock market studies) are based on queueing techniques. Queueing behavior plays an important role in short-term market dynamics. Kiesel and Luckner (2018) is the only reference in the electricity continuous trading intraday market subject that models market order arrivals by a stochastic process called Hawkes process. In markets with a limit order book structure, the timing of order arrivals play a key role because these market orders are the ones that may change the mid price and bid-ask spread. By empirical analysis, Kiesel and Luckner (2018) illustrate that a Hawkes process with exponential baseline intensity and exponential excitement function is able to capture the dynamics of market order arrivals very well.

Thus far, Von Selasinsky (2016) is the only and the most comprehensive reference in simulating continuous trading intraday electricity markets. Since this reference is inspirational to many ideas mentioned in this paper, its approach will be brifely summerized here. To find the initial point for the intraday market, the first step is to clear the day-ahead market. The day-ahead result determines the dispatched and non-dispatched generators as well as satisfied and unsatisfied consumers. The continuous structure of the intraday market is modeled by discrete time steps; meaning that for a given hour in the future ten pre-defined time steps and thus ten possibilities to balance forecast errors are considered. In other words, Von Selasinsky (2016) assumes that for each day-ahead clearing of a future trading hour, the wind forecast can be updated ten times. At the first time step, market participants decide to offer buy or sell order based on the results of the day-ahead market. Then, by a very innovative procedure, an intraday offer pair (quantity,price) is calculated for each market participant. The resulting offers are utilized to generate an order book for the first time step by sorting bids in descending and asks in ascending order with respect to their price. Von Selasinsky (2016) also assumes that a central renewables manager (CRM) tries to balance the cumulative forecast errors from all renewable producers. Therefore, when the limit order book is created, with respect to the direction and the magnitude of the forecast error, the CRM decides to either sell or buy a quantity and hence start to be matched with the highest priority orders from the limit order book. Next, the matched orders will be stored and the position (quantities) of cleared market participants will be updated to be used for the next time steps. A similar simulation procedure is repeated for nine more time steps when forecast errors are updated.

Even though Von Selasinsky (2016) made outstanding contributions to continuous trading simulation, especially in calculating optimal price and quantity of orders submitted to the intraday market by different types of market participants (generators and consumers), his model is still not able to capture the dynamic structure of entering the orders, adding them to the list, matching, and many other characteristics of the limit order book. Moreover, the forecast errors of all intermittent producers are balanced by a central manager and this authority, irrespective of the submitted order prices, just try to trade the imbalance quantity after each updated forecast. Hence, firstly each intermittent generator cannot decide for its own imbalances and secondly by this approach the CRM has to balance forecast errors whenever it receives the updated information. So, no trade-off between risk and profit of intermittent producers is allowed in this decision making process.

In this paper, in contrast to the very advanced price and quantity setting model devised by Von Selasinsky (2016), very simplified assumptions are made on price and quantity decisions. Instead, I focus on the limit order book modeling wherein market participants (they can be any type of intermittent and conventional generators, elastic consumers and even financial traders) randomly (based on a uniform distribution) submit market or limit orders with random quantities chosen from their residual capacity or cleared capacity (depending on ask or bid order submission) and with their day-ahead marginal cost as the submitted price. The model is able to manage the order arrivals, their addition to the list (as limit order) or matching them with the best available opposite order (market order), store the matched trades, update the quantities of matched orders and lastly to accept part (or whole) of matched orders to maintain the feasibility of the transmission network with respect to the nodal constraints of the network. Hence, the procedure allows for taking into account congestion management by checking trades against available remaining capacity, and curtailing trades when the capacity is not sufficient. By this approach, the stochastic process of order arrivals is still very simplified and independent of the current state of the limit order book but it provides a solid fundamental model for the limit order book. Then the other characteristics of the limit order book like dependence of order arrivals to the state of the limit order book, modeling intermittent entrance by the time of receiving updated forecasts and advanced trading startegies of non-intermittent market participants - like their decision to trade or not, submit ask or bid orders, and (quantity,price) pair decisions - can be attached to the fundamental basis provided in this paper.

5.3 The reasons for participating in the intraday market and price impacts

As I explained before, the intraday market lets market participants correct their day-ahead decision and adjust their quantity and price appertaining to either their own deviations or new information extracted from the market. In this section, several motivations for intraday market involvement will be discussed. Hagemann (2013b) studied empirically the effect of diverse factors over intraday market prices which are reflecting the market participants willingness to involve in this market. His hypothetical price determinants are:

1. Unplanned power plant outages
2. Forecast errors from intermittent renewable energy sources
3. Load forecast error
4. Cross-border trading

The empirical analysis on German data confirms that forecast errors from intermittent renewables, especially wind, have the highest impact on the average price.

Neuhoff et al. (2016c) mention that in the case of power plant outages, which need large adjustments, market participants are more willing to negotiate bilaterally. In this fashion, a buyer is allowed to identify its needs for consecutive hours and the seller of (this large flexibility) is allowed to do more comprehensive adjustments of its operational schedules, e.g. the start-up of new units. Therefore, in this paper we exclude the possibility of flexibility trading owing to outages.

In the following subsections, it will be illustrated how prices and/or quantities submitted to the limit order book are influenced by these elements.

5.3.1 Price setting decisions in the intraday market due to the intermittent generators' forecast error

For better analyzing the intraday market, the day-ahead market results can be utilized. Figure 5.1 illustrates conventional supply and demand curves for a given hour in the day-ahead auction. Since in the supply curve the generators' offers are ranked according to increasing prices, this curve is referred to as the merit order curve. Renewables have a very low marginal cost. Hence, they are found at the bottom of the curve. Then respectively, base load, mid-load and peak-load power plants are stacked.

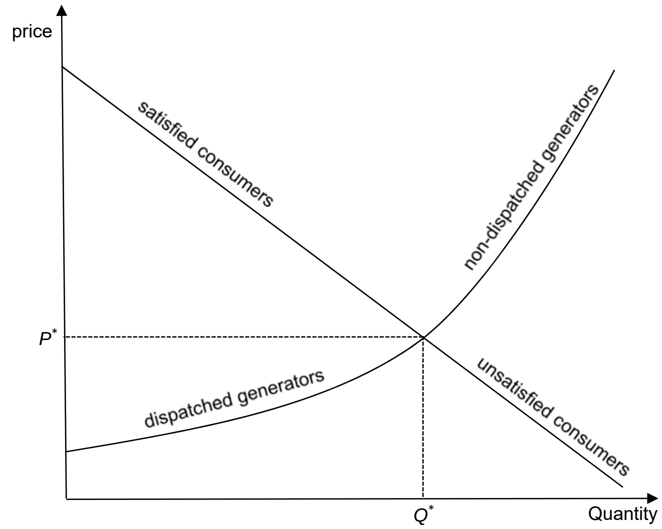

Figure 5.1. Day-ahead auction for a given hour (Von Selasinsky (2016))

The bids received from consumers are sorted descendingly (with respect to price). In uniform price markets, the intersection of the supply and demand curves determines the clearing price. It is generally assumed that under full competition, all market participants offer their true valuation which is the marginal cost of production for generators and the willingness to pay for consumers. As can be seen from Figure 5.1, dispatched generators and satisfied consumers are those accepted to produce and consume at the day-ahead clearing price. Generators/consumers with offer prices above/below the clearing price are called non-dispatched generators/unsatisfied consumers. It is assumed that all accepted and non-accepted day-ahead participants can take part in the intraday market. After revealing the day-ahead market results, we can divide the market participants into two groups: Buyers (submit bid) and sellers (submit ask) in the intraday market.

Dispatched generators sold in the day-ahead market, hence they are able to buy back quantities in the intraday market by submitting a bid. Similarly, since unsatisfied consumers were not able to buy in the day-ahead market, they can buy their required quantities in the intraday market by submitting a bid. Satisfied consumers bought in the day-ahead market, thus they can sell the quantities they bought before by submitting an ask in the intraday market. Finally, non-dispatched generators did not succeed in selling in the day-ahead market, therefore, the intraday market provides a new opportunity to sell (ask).

Figure 5.2 demonstrates that by vertical rotation of the demand function around the day-ahead equilibrium, dispatched generators and unsatisfied consumers can be grouped as bidders, while non-dispatched generators and satisfied consumers are able to submit ask.

Now the question is how do market participants set the prices in a continuous intraday market? By submitting the true valuation of the electricity bought or sold, which is called the indifference price, market participants would not make a profit from the transaction, meaning that they are indifferent between staying in the current position or changing this position. Nevertheless, the incentive to participate in the intraday market is to earn more profits not just to be indifferent. Therefore, in a competitive continuous intraday market a profit-making strategy for generators and consumers is to bid below their true valuation for quantities they buy and to ask above their true valuation for quantities that they sell. It should be noted that the profit-making strategy should not be confused with market power issues, seeing that they are a straightforward consequence of continuous trading design. Forecast

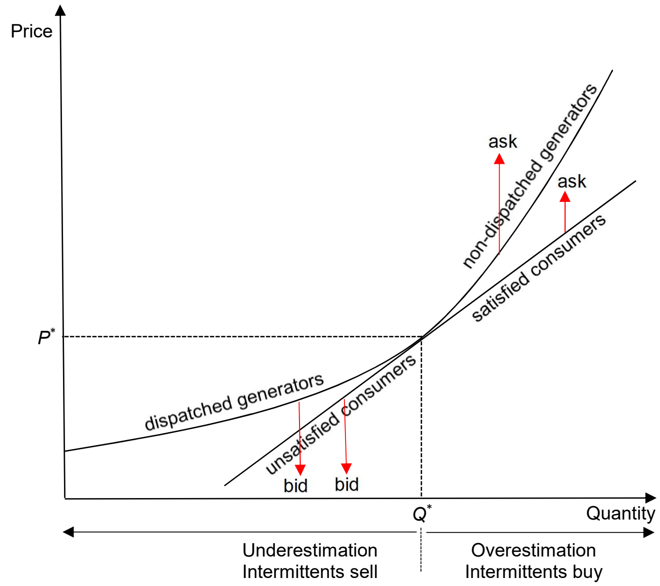

Figure 5.2. Framework for analysing the intraday market (Von Selasinsky (2016))

errors from intermittent renewables is one of the main stimulating factors for other generators and consumers to trade in the intraday market with the aim of profit increment.

If the output from renewables is underestimated, they are eager to sell electricity, and the market participants on the left side of $Q*$ can submit bids to buy their quantities in the intraday market. In order to have a profitable trade, the bidders have to bid below their day-ahead offer price (bid arrows in Figure 5.2). In this fashion, if the bidder is a generator, it is able to get the quantities cheaper from the intraday market than from its self-production. Similarly, for a consumer it is profitable to buy electricity when prices are below its willingness to pay.

Conversely, an overestimation of renewable outputs means that they have to buy the difference in the intraday or balancing market. Thus, if the agents on the right side of $Q*$ ask above the price of their unsuccessful day-ahead offer, not only their marginal cost is covered but also some profit is attainable. Satisfied consumers will only sell the quantities they acquired in the day-ahead market if at least their true valuation is paid.

Thus far, we have mentioned that in the first order placements in the intraday market the buyers bid below and the sellers ask above their marginal costs and willingness to pay. But the main feature of continuous trading is to let market participants trade electricity for a given hour in the future multiple times. For instance, intermittent renewables like wind generators may decide to react to updated forecasts whenever they get a new one. Then they try to buy (in the case of overestimation) or sell (in the case of underestimation) electricity for a given hour in the future. Hence, they provide this opportunity for other generators and consumers to modify their intraday decisions in order to make more profit. Even though the possibility of trade among all market participants could exist, the probability of this occuring is not very high. As an illustration, since a non-dispatched generator has higher marginal cost than a dispatched one, its ask price is probably higher than the willingness to pay of a dispatched generator.

5.3.2 Intraday market trading for relieving congestion

Different congestion management approaches in day-ahead and balancing markets in European power markets create inefficiencies within and between countries as follows:

- Within countries: As the network is simplified in the day-ahead market, the value of generation at different locations is not recognized thoroughly by this market, resulting in gaming opportunities and inefficient dispatch.
- Between countries: capacity allocation of transmission across zones is treated differently from intra-zonal dispatch, which gives incomplete information on the state of the transmission network and usually ending up with underutilization of the network.

Hence, if the EU commission, electricity regulatory forum or any other related political economics institutions still put their foot down to operate simplified networks in the day-ahead market, there is still the possibility to relieve congestion resulting from day-ahead schedules in the intraday market. In this paper, we suggest a congestion management method to have feasible trades in the intraday market but we are not necessarily attaining the optimal nodal solution.

5.4 Model

5.4.1 Modeling assumptions

In a limit order market, transaction prices are determined by the interaction of incoming orders with the current state of the order book. So, in order to have a proper model of the price formation and stochastic properties of prices, we need to have a better perception of this interaction.

Owing to the inherent complexity of limit order markets, developing a tractable model may be hindered by many simplifying assumptions:

1. The arrival of orders of any type (bid, ask, limit order, market order) as well as the type of entrant agent (generator or consumer) is based on simple uniform distribution in (0,1). If we want to see the relation between incoming orders with the current state of the limit order book then we have to work on this assumption.
2. Market participants submit their (price,quantity) pair without using information about the current state of the limit order book. This situation usually happens in very active markets in which the order book changes before a reaction of an agent can be transmitted (which is not the case at least in current intraday markets). Hence, by this assumption the expected order arrival rates will be independent of the order book state. In the more advanced case, we need a self-exciting process to show that the market participants' decisions are not independent of the state of the limit order book, because they watch the current prices in the list, the spread or average price, then decide to enter or wait and choose the (price,quantity) pair. It seems that a Hawkes process is very suitable to model the self-exciting behavior of the limit order book. In this paper, the dependence of order arrivals on the current state of the limit order book is relaxed and will be investigated in future research.
3. The independence assumption let us assume that agents just submit their marginal cost (MC) or willingness

to pay (MB) as the price, and quantities are determined randomly based on the agents' available or cleared capacity in previous trades. Hence, in this paper, I avoid to focus on the profit making strategies of agents by finding optimal price and quantity values.

In general, these assumptions can be interpreted as a market with zero information flow.

5.4.2 Mathematical model

When a market participant submits an order, three important factors **price**, **quantity** and **time** must be considered. Hence, an ordered triple $x = (p_x, q_x, t_x)$ represents that an agent has submitted an order x with price p_x, quantity q_x at time t_x to trade up to q_x units at a price not lower than p_x to sell or not higher than p_x to buy.

The third assumption in Section 5.4.1 mentions that limit order prices are placed from a price set $P = \{MC_{g_1}, MC_{g_2}, ..., MC_{g_G}, MB_{d_1}, MB_{d_2}, ..., MB_{d_D}\}$. G and D are respectively the total number of generators and consumers.

At time zero, the limit order book is empty. At time t, the state of the order book is kept track of with a continuous time process $X(t) = (X_{MC_{g_1}}(t), ..., X_{MC_{g_G}}(t), X_{MB_{d_1}}(t), ..., X_{MB_{d_D}}(t)), t \geqslant 0$, where $\mid X_p(t) \mid$ is the number of limit orders at price $p \in P$.
If $X_p(t) < 0$, then there are $-X_p(t)$ bid orders at price p;
If $X_p(t) > 0$, then there are $X_p(t)$ ask orders at price p.

In the limit order markets, we are interested in the best bid and best ask prices stored in the order book. Lets define $p_A(t)$ as the lowest (i.e. best) ask price at time t:
$p_A(t) = Min(\{p \in P \mid X_p(t) > 0\} \cup \{p_{cap}\})$
And $p_B(t)$ as the highest (i.e. best) bid price at time t:
$p_B(t) = Max(\{p \in P \mid X_p(t) < 0\} \cup \{0\})$

When the ask list in the order book is empty, an ask price of p_{cap} (which is the market cap price) is forced and when there is no bid order, a bid price of 0 is forced. Without loss of generality, we can assume that at any time t, the order book consists of a queue of unexecuted sell orders with sorted prices $\alpha_1(t), \alpha_2(t), ...$ and another queue of unexecuted buy orders with sorted prices $\beta_1(t), \beta_2(t), ...$ waiting to be matched with incoming orders. These prices are actually reindexed such that $\alpha_1(t) = p_A(t)$ and $\beta_1(t) = p_B(t)$. Hence, the prices will satisfy the inequalities:
$... \leqslant \beta_2(t) \leqslant \beta_1(t) < \alpha_1(t) \leqslant \alpha_2(t) \leqslant ...$

Whenever a new order is submitted, the order book will be revised according to the following rules:

1. If the new order is a buy (bid) at the price p_b and quantity q_b, at time t, then:
   - If $p_b \geqslant p_A(t-1)$, the new bid order becomes a market order and is immediately matched with the current best ask (lowest ask). Then the matched price and quantity are:
     $p_{matched} = p_A(t-1)$
     $q_{matched} = Min(q_b, q_A(t-1))$
     Thus, the updated lowest ask price (in the case that the whole order quantity is not matched)
     If $q_{matched} = q_b$, then $p_A(t) = p_A(t-1)$
     If $q_{matched} = q_A(t-1)$, then $p_A(t) =$ the next lowest ask price in the list $(\alpha_2(t))$

- If $p_B(t-1) < p_b < p_A(t-1)$, then the new bid order will be a buy limit order which places at the top of the bid list causing a change in the highest bid price at time t; $p_B(t) = p_b$, $q_B(t) = q_b$.
- If $p_b \leqslant p_B(t-1)$, then the new bid order will be a buy limit order (and will be added to the bid list) but will not change the highest bid price; $p_B(t) = p_B(t-1)$

2. If the new order is a sell (ask) at the price p_a and quantity q_a at time t, then:

- If $p_a \leqslant p_B(t-1)$, the new ask order becomes a market order and is immediately matched with the current best bid (highest bid). Then the matched price and quantity are:
  $p_{matched} = p_B(t-1)$
  $q_{matched} = Min(q_a, q_B(t-1))$
  Hence, the new highest bid price is updated as follows:
  If $q_{matched} = q_a$, then $p_B(t) = p_B(t-1)$
  If $q_{matched} = q_B(t-1)$, then $p_B(t) =$ the next highest bid price in the list $(\beta_2(t))$
- If $p_B(t-1) < p_a < p_A(t-1)$, then the new ask order will be an ask limit order which places at the top of the ask list causing a change in the lowest ask price at time t; $p_A(t) = p_a$, $q_A(t) = q_a$.
- If $p_a \geqslant p_A(t-1)$, then the new ask order will be an ask limit order (and will be added to the ask list) but will not change the lowest ask price; $p_A(t) = p_A(t-1)$

In this paper, order arrivals are not only taken from a stochastic process but also the available/already cleared capacity of market participants from the day-ahead market and previous intraday trades are considered to decide about bid or ask order submissions. The details of the stochastic process will be explained in the simulation section.

5.4.3 Simulation of the continuous intraday market

Figure 5.3 demonstrates the simulation procedure of the continuous intraday market. The steps are as follows:

1. Day-ahead results: after solving the day-ahead market based on formulation 5.1, information about cleared quantities, q_g^{DA*} and q_d^{DA*}, of generators and consumers respectively, as well as zonal prices are announced

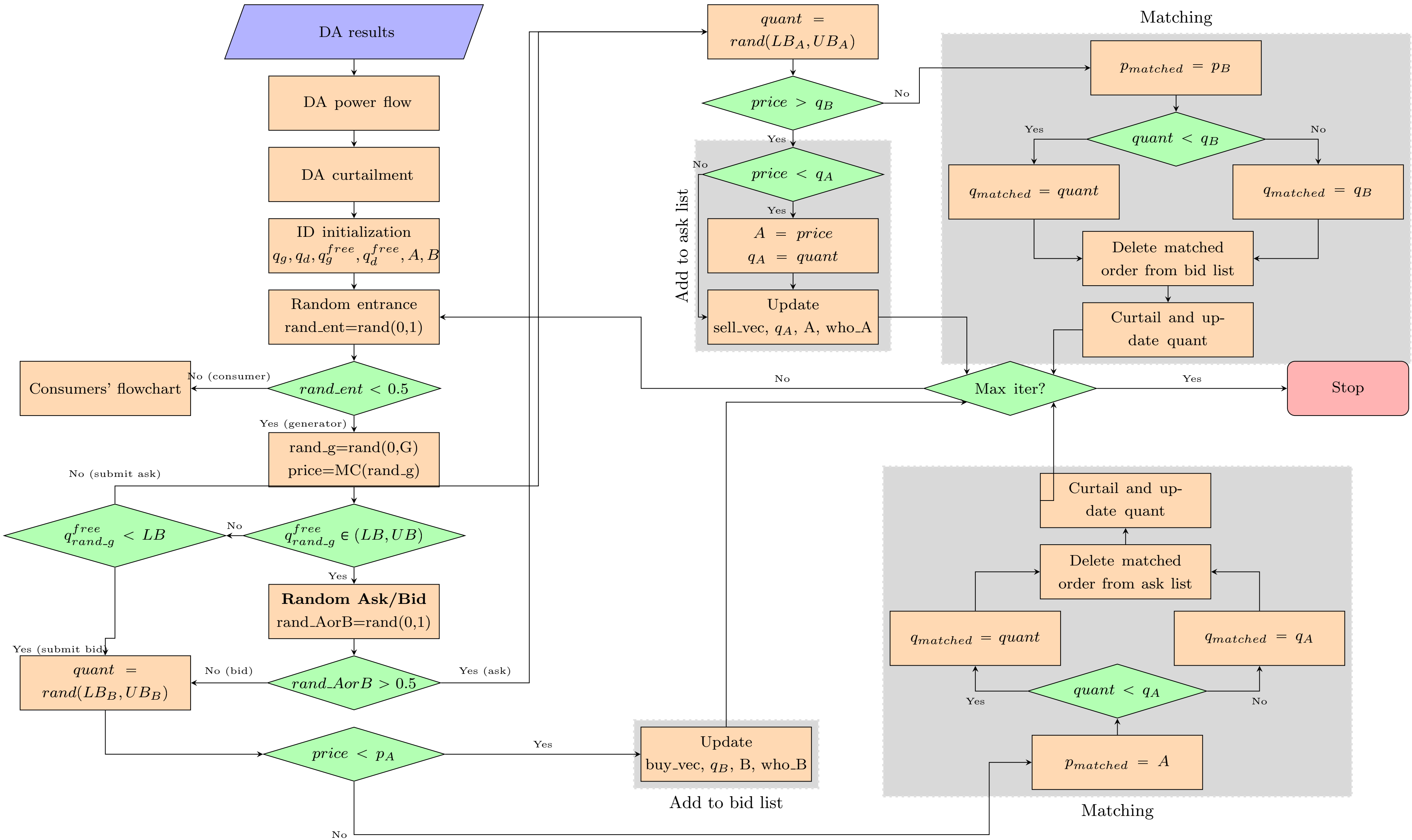

Figure 1. Flowchart for intraday market simulation procedure

by the market operator (power exchange).

$$
\begin{aligned}
&\text{Maximize}_{q_g^{DA}, q_d^{DA}, f_e} && \sum_{d \in D} B_d(q_d^{DA}) - \sum_{g \in G} C_g(q_g^{DA}) && && (5.1a)\\
&\text{subject to:} && q_g^{DA} \in FR^{DA}\ ,\ q_d^{DA} \in FR^{DA} && && g \in G, d \in D && (5.1b)\\
& && NI_z = \sum_{g\, \in\, z} q_g^{DA} - \sum_{d\, \in\, z} q_d^{DA} && : (\lambda_z) && z \in Z && (5.1c)\\
& && NI_z = \sum_{e:\omega_0(e)=z} f_e - \sum_{e:\omega_1(e)=z} f_e && && z \in Z && (5.1d)\\
& && -ATC_e \leqslant f_e \leqslant ATC_e && && e \in E && (5.1e)
\end{aligned}
$$

The objective function (5.1a) maximizes the social welfare of the power system. $C_g(q_g^{DA})$ and $B_d(q_d^{DA})$ show the cost and benefit functions of generators and consumers, respectively. The constraint (5.1b) reflects the production/consumption capacity constraints of generators and consumers or in general it can show any constraint on market participants in the feasible region FR^{DA}. NI_z declares the net injection (outflow (if $NI_z > 0$)/ net inflow (if $NI_z < 0$)) of power to zone z. The day-ahead power balance constraint at each zone $z \in Z$ is demonstrated by equation (5.1c), meaning that production minus consumption with positive/negative sign equals to the net outflow/inflow at each zone. Therefore, the shadow price λ_z of this equation is interpreted as the day-ahead clearing price of zone z. Unlike nodal day-ahead market, just commercial flows which do not reflect physical network constraints are modeled in the zonal day-ahead market. For every adjacent zones which are connected by physical connections l, there exists a cross-border interface $e \in E$ which conveys commercial flows between zones. Corresponding to each interface e, there is a flow $(f_e)_{e \in E}$. If ω_0 and ω_1 show the starting and ending zones of interface e and $f_e > 0$, then it means that commercial flow is flowing from ω_0 to ω_1. Constraint (5.5e) shows the cross-border trade capacities (ATC) over the cross-zonal interfaces. Thus, the day-ahead dispatch model (5.1) can be elucidated as a partly network-constrained auction where the cheapest generators and the consumers with the highest willingness to pay are cleared. Due to the network simplification at day-ahead stage, most probably the day-ahead solution is not satisfied by the physical network constraints and therefore is not a feasible initial trade for intraday market.

2. Day-ahead power flow: in order to have feasible trades in the intraday market, the system operator has to check the power flows of the physical transmission lines for the day-ahead results, by checking the following equations:

$$
\begin{aligned}
& NI_n = \sum_{g\, \in\, n} q_g^{DA*} - \sum_{d\, \in\, n} q_d^{DA*} && n \in N && (5.2a)\\
& f_l = \sum_{n \in N} PTDF_l^n \times NI_n && l \in L && (5.2b)\\
& \mid f_l \mid \leqslant f_l^{max} && l \in L && (5.2c)
\end{aligned}
$$

NI_n in equation (5.2a) shows the net injection of power into node n for optimal day-ahead solution q_g^{DA*} and q_d^{DA*}. Nodes of the network are connected by a set of physical transmission lines L. Corresponds to each line l, there is a flow $f = (f_l)_{l \in L}$. To calculate the physical power flow over each line l, the PTDF-based formulation (5.2b) can be utilized. $PTDF_l^n$ is the power transfer distribution factor, which states how much power flows through line l if 1 MW is injected in node $n \in N$ and is taken out in the reference node. By inequalities (5.2c) flows are forced to be in the capacity limit of the lines. If the day-ahead schedule is not satisfying the power flow constraints (5.2c), then the congested lines must be saved and optimal curtailment is done.

3. Day-ahead curtailment: we need to have a feasible flow before intraday trades occur. Because it is very probable that a matched trade in the intraday market is totally curtailed due to the infeasibilities caused by other market participants in the day-ahead stage. Thus, the transmission system operator (TSO) is running the following curtailment model:

$$\text{Minimize}_{q_g^{curt}, q_d^{curt}} \quad \sum_{g \in G} q_g^{curt} + \sum_{d \in D} q_d^{curt} \tag{5.3a}$$

$$\text{subject to:} \quad NI_n = \sum_{g \in n} (q_g^{DA*} - q_g^{curt}) - \sum_{d \in n} (q_d^{DA*} - q_d^{curt}) \qquad n \in N \tag{5.3b}$$

$$\sum_{n \in N} NI_n = 0 \tag{5.3c}$$

$$f_l = \sum_{n \in N} PTDF_l^n \times NI_n \qquad l \in L \tag{5.3d}$$

$$| f_l | \leqslant f_l^{max} \qquad l \in L \tag{5.3e}$$

$$0 \leqslant q_g^{curt} \leqslant q_g^{DA*} \qquad g \in G \tag{5.3f}$$

$$0 \leqslant q_d^{curt} \leqslant q_d^{DA*} \qquad d \in D \tag{5.3g}$$

The objective (5.3a) minimizes the total curtailment of the day-ahead quantities. It is assumed that all generators and consumers have equal value of lost of generation and load, hence the weight of q_g^{curt} and q_d^{curt} is equal to 1. NI_n in equation (5.3b) is the net injection of power into node n when the day-ahead solution is curtailed. Equation (5.3c) guarantees that the sum of net injections over all nodes in a lossless system must be equal to zero. Constraints (5.3d) and (5.3e) have the same interpretations as (5.2b) and (5.2c). Finally, (5.3f) and (5.3g) guarantee that the curtailed quantities do not exceed the original production and consumption in the day-ahead solution. After finding the curtailed quantities, generation and consumption is updated as follows:

$$q_g = q_g^{DA*} - q_g^{curt} \qquad q_g^{free} = q_g^{max} - q_g \qquad g \in G \tag{5.4a}$$

$$q_d = q_d^{DA*} - q_d^{curt} \qquad q_d^{free} = q_d^{max} - q_d \qquad d \in D \tag{5.4b}$$

4. Intraday initialization: The updated feasible schedules q_g and q_d for all g and d are conveyed to the intraday market. However, at the opening of the intraday market (for a specific delivery hour) the limit order book is empty. If generators enter the intraday market, then they may submit part of their cleared (and curtailed) quantity for buy and residual capacity (which equals to q_g^{free}) for sell, while consumers may submit a portion of their residual capacity q_d^{free} for buy and cleared quantity q_d for sell. Moreover, since at the beginning, the limit order book is empty, I initialize the prices such that the ask price is set to the price cap and the bid price is set to zero.
5. Random entrance: when the intraday market is opening, there could be several reasons (Section 5.3) for the market participants to enter into the intraday market. This is the part that is difficult to model because we have to model them based on the limit oreder book state. We have to make a chaos from the day-ahead market. For example, a consumer may enter first because of a load forecast error, or a wind generator may enter first because of the updated forecast it gets, but in all these cases it is important to consider what would be their submitted price and quantity and how prices are evolving based on the latest information which

is attainable from the limit order book. The orders can either enter at a constant rate (like in the Poisson process) or be governed by an intensity function. However, in reality it is often known that the arrival of an event increases the likelihood of observing events in the near future. An earthquake aftershock event is a very good example for this type of events. It seems that a class of processes in which the arrival rate explicitly depends on past arrivals is perfectly fitted to the limit order book model and the most well-known self-exciting process is the Hawkes process. As explained in the second assumption in Section 5.4.1, in this paper it is assumed that the order arrivals are independent of the state of the limit order book and the order arrival is modeled by a very simple uniform distribution. A random number, *rand_ent*, is picked up from (0,1). A number less than 0.5 means that a generator enters while a number greater than 0.5 means that a consumer enters to the intraday market.

6. Like in stage 5, a generator (*rand_g*) or a consumer (*rand_d*) is sampled uniformly at random, from the integers 1 to G or 1 to D and therefore, by assumption 3, its MC (for generator) or MB (for consumer) will be the submitted price. Hence, in this paper the price submission is not in accordance with the ideas mentioned in Section 5.3.1 and the optimal bidding of market participants to the intraday market is neglected.
7. As mentioned before, when an agent decides to submit an order in the intraday market, the pair (price,quantity) must be submitted. The amount of residual capacity q_g^{free} (or q_d^{free}) is a determining factor when submitting bid or ask orders, and several cases may happen. For generators, if the residual capacity q_g^{free} is close to zero (LB is equal to 5, meaning that all quantities in the limit (0,5) are considered as almost zero) then g does not have any extra capacity to sell and the only option is to buy. Hence, any random number in $[LB_B, UB_B] = [5, q_g]$ can be submitted as the bid order quantity. If q_g^{free} is close to the capacity limit (UB is equal to $q_g^{max} - 5$, meaning that all quantities in $[q_g^{max} - 5, q_g^{max}]$ are considered as quantities close to capacity), it means that g has not sold anything yet, and if g decides to enter now, then the only option is to sell. Thus, any random number in $[LB_A, UB_A] = [5, q_g^{max}]$ can be submitted as the sell order quantity. Finally, if the residual capacity $q_g^{free} \in (5, q_g^{max} - 5)$, then g can randomly decide to submit ask or bid orders.
8. After deciding on bid or ask orders, price and quantity submission, the procedure of matching or adding to the list is exactly what is explained in Section 5.4.2. If matching occurs, then the opposite best order must be updated, either deleted from the list or still stay in the list with updated quantity. Then the matched quantity and their two related locations (nodes) in the network is sent to the TSO. The TSO checks the feasibility of this trade and solve the curtailment problem (5.3) if necessary, by replacing $q_{matched}$ instead of q^{DA*}.

5.5 Illustrative example

5.5.1 Data

In this section, a small 6-node system is used to intuitively illuminate the main characteristics of the previously discussed intraday market model.

Figure 5.4 depicts a 6-node system which consists of 6 nodes $n \in \{1, ..., N = 6\}$, 3 generators $g \in \{1, ..., G = 3\}$ placed respectively at nodes 1,2 and 5, 3 consumers $d \in \{1, ..., D = 3\}$ located at nodes 3,4 and 6, and finally 8 lines $l \in \{1, ..., L = 8\}$. The capacity of the lines is shown in the figure, and the reactance of every line is assumed to be equal to 1. This nework is decomposed into to zones z_1 and z_2.

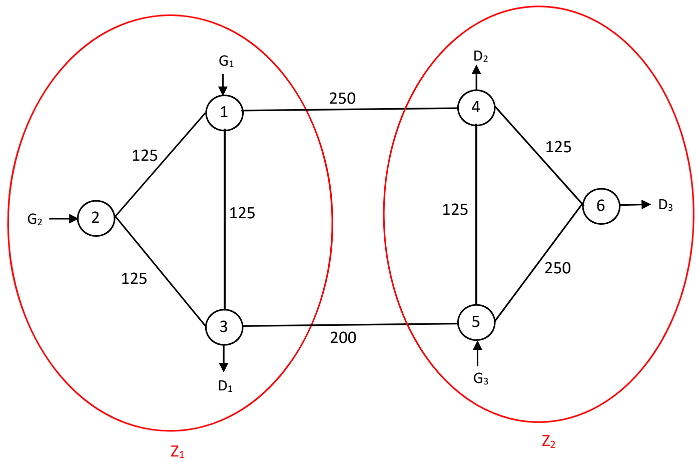

Figure 5.4. 6-node network configuration

Data for the generators and consumers is collated in Table 5.2, where q_g^{max} and q_d^{max} are the generator g and consumer d capacities . MC_g is the marginal cost of production of generator g and MB_d is the marginal benefit of consumption of consumer d, which is assumed to be their offer price in the day-ahead as well as intraday market.

Table 5.2. Generators and consumers' data

Generators	MC (€ $/MWh$)	q_g^{max}	Consumers	MB (€$/MWh$)	q_d^{max}
G_1	12	450	D_1	23	450
G_2	20	350	D_2	21	400
G_3	17	400	D_3	30	350

5.5.2 Day-ahead market results

In the day-ahead market, the zonal configuration with two zones and zero transmission capacity between them is considered, meaning that $ATC = 0$, which is the worst case with respect to considering the transmission limitation between zones.

The day-ahead result along with the power flows over the physical lines - which are calculated with respect to the day-ahead net injections at each node - is illustrated in Figure 5.5. As the result shows, the day-ahead market culminates in an infeasible network solution due to the violation of lines l_{13} and l_{46} capacity constraints. Therefore, for the purpose of having feasible trades before the intraday market, the day-ahead result has to be curtailed by curtailment problem (5.3) to reach a feasible solution. The day-ahead curtailed solution is depicted in Figure 5.6. Hence, thus far a feasible starting point for the intraday market is extracted and the corresponding social surplus equals to 7713 €.

5.5.3 Continuous intraday trading environment

At the beginning of the intraday market, the limit order book is empty. Assume that after a while, D_1 decides to enter (as mentioned before, the reason for D_1's participation is not paid attention to here, however in a more advanced model we have to consider why this participant enters the intraday market).

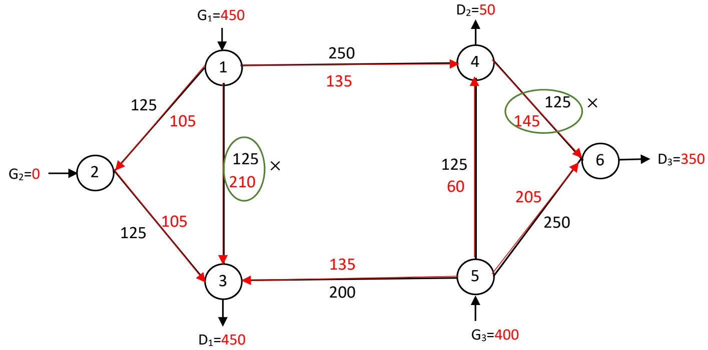

Figure 5.5. Day-ahead result for 6-node example

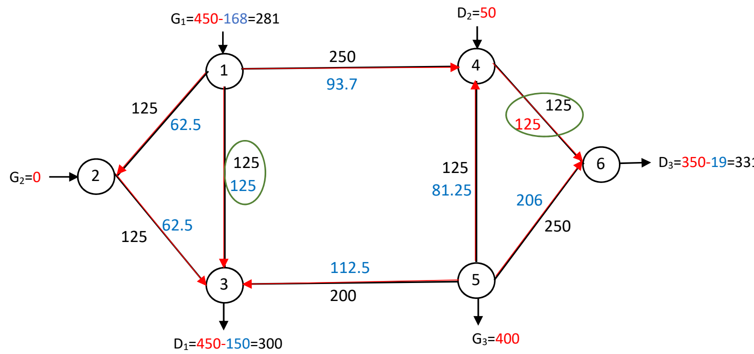

Figure 5.6. Day-ahead curtailed result

As Figure 5.6 demonstrates, D_1 is assigned to consume 300 MW after the day-ahead curtailment, hence its available capacity is equal to 150 MW. D_1 can submit both ask and bid orders. Without knowing the reason of its participation, we assume that D_1 submits an ask order with price equal to its willingness to pay, which is 23, and a random quantity from (0,300), because submitting an ask means that D_1 wants to decrease its consumption by selling part of the 300 MW that had been cleared before.

Then as a second entrant, D_2 enters by submitting a bid order with price equal to 21 and a random quantity from (0,350), meaning that it wants to increase its consumption from 50 MW.

Now assume that the third generator, G_3, is interested in buying back a portion of its day-ahead production

	who	Ask		who	Bid		
		quantity	price		quantity	price	
a	D_1	135	23				b

Figure 5.7. Limit order book after first order submission

	who	Ask		who	Bid		
		quantity	price		quantity	price	
a	D_1	135	23	D_2	205	21	b

Figure 5.8. Limit order book after second order submission

	who	Ask		who	Bid		
		quantity	price		quantity	price	
a	D_1	135	23	D_2	205	21	b
				G_3	382	17	

Figure 5.9. Limit order book after third order submission

	who	Ask		who	Bid		
		quantity	price		quantity	price	
	~~G_2~~	~~31~~	~~20~~	~~D_2~~	~~205~~	~~21~~	matched
a	D_1	135	23	G_3	382	17	b

Matched quantity = 31
Matched price = 21

Figure 5.10. Limit order book after fourth order submission

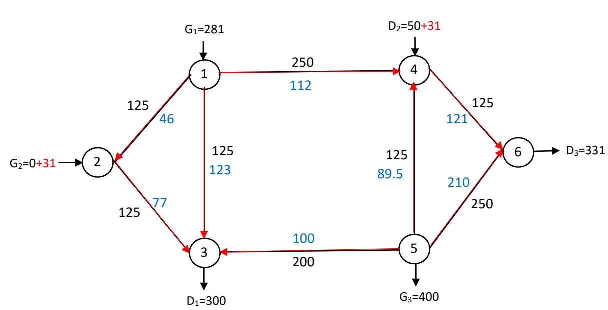

Figure 5.11. Power flows after first matching

(it does not have an option to submit an ask, because it sold all its capacity in the day-ahead market, therefore if it decides to trade, the only possibility is just to submit a bid). Then it submits a bid with price 17 and random quantity 382 from the interval (0,400). Since its offered price is 17, which is lower than the highest bid price, G_3's order is placed in the second priority after D_2's order, and still 21 is the highest bid price.

If G_2 enters as a fourth entrant by submitting an ask order with price of 20 and a random quantity from (0,350), since the asked price of the new arrival is lower than the current highest bid (which is 21), then matching occurs between G_2 and D_2. The matched price and quantity are respectively 21 and 31. Thus, G_2 is removed from the ask list while D_2 can stay in the bid list with a price and quantity pair of (21,174), or it can be cancelled after matching, in which case the highest bid price goes down from 21 to 17 and the spread increases.

After each matching, the power flows over the physical lines can be calculated and in the case of violation, a partial or full curtailment of the matched trade can be done by the system operator. The Latest power flows after adding the new matched trade is shown in Figure 5.11. None of the lines are violated, so no curtailment is needed, and the updated quantities are $q_{G_2} = 31$ and $q_{D_2} = 81$. By this trade the social surplus is raised by 31€ ($(21 - 20) \times 31$) and the total reaches 7744€.

Now, the simulation procedure is used to compare the two following cases:

- Lower number of entrances: it is assumed that 200 entrances occur which means that on average an entrance occurs every 7 minutes. Then, in total, the intraday market trades raise the social surplus by 461€ and the total social surplus of the day-ahead and intraday market reaches 8174€.
- Higher number of entrances: it is assumed that 1000 entrances occur which means that on average an entrance occurs every 1.5 minutes. Then, in total, the intraday market trades raise the social surplus by 754€ and the total social surplus of the day-ahead and intraday market reaches 8467€.

These solutions can be compared with the optimal nodal benchmark case with the following formulation:

$$\text{Maximize}_{q_g^{DA}, q_d^{DA}, f_l} \quad \sum_{d \in D} B_d(q_d^{DA}) - \sum_{g \in G} C_g(q_g^{DA}) \tag{5.5a}$$

$$\text{subject to:} \quad q_g^{DA} \in FR^{DA}\ ,\ q_d^{DA} \in FR^{DA} \qquad g \in G, d \in D \tag{5.5b}$$

$$NI_n = \sum_{g \,\in\, n} q_g^{DA} - \sum_{d \,\in\, n} q_d^{DA} \qquad : (\lambda_n) \qquad n \in N \tag{5.5c}$$

$$NI_n = \sum_{l:\nu_0(l)=n} f_l - \sum_{l:\nu_1(l)=n} f_l \qquad n \in N \tag{5.5d}$$

$$| f_l | \leqslant f_l^{max} \qquad l \in L \tag{5.5e}$$

If ν_0 and ν_1 show the starting and ending nodes of line l and $f_l > 0$, then it means that power is flowing from ν_0 to ν_1. Optimal nodal power flow result is depicted in Figure 5.12. The best possible social surplus can be achieved by the nodal result which is equal to 8912.5€.

An interpretation of these results demonstrate that if it was an aim to utilize the continuous trading intraday market to resolve congestion issues, then a very liquid market is needed but still the optimal nodal solution will not attained, with only bilateral trading.

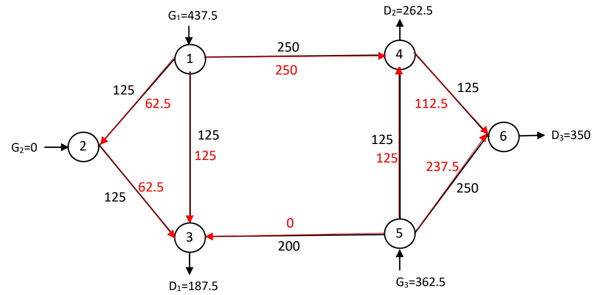

Figure 5.12. Optimal nodal power flow result

5.6 Suggestions for future research

With a fundamental basis for a continuous trading model, there are many possibilities to develop the model further to analyze specific issues in a continuous trading environment. Some examples are given in the next two sections.

5.6.1 Model intermittent producers entrance into the intraday market

The reasons for participating in the intraday market is mentioned in Section 5.3 but it has not been explicitly modeled in this paper. An obvious reason for trading in intraday market is updated forecasts for intermittent generation sources. Among the few references that suggest optimal trading strategies for wind producers in intraday markets, Garnier and Madlener (2015)'s method considers the continuous structure of the intraday market in the best way. They formulate an intraday bidding strategy for wind and solar producers to maximize the value of trade under price uncertainty and production forecast error. Whenever an intermittent producer receives an updated forecast for delivery hour t, it can either decide to trade immediately or postpone it to the next trade window of updated forecasts. Their method combines the trade value concept with an option valuation and dynamic programming to optimize quantity and timing decisions of an intermittent producer to balance their updated forecast errors. The main important issue related to the intermittent producers' participation in the intraday market is their price submission with respect to the fact that their marginal cost is almost zero. The output of the Garnier and Madlener (2015) model is also just the "optimal quantity" and "trade/or not trade" decision at the time of receiving an updated forecast. This suggests that intermittent producers can just submit "market order" not "limit order". In other words, if the result of the Garnier and Madlener (2015) model says that trade is valuable now, the intermittent producer submits a market order, otherwise no action is taken. As mentioned before, in market orders an entrant agent's quantity is just matched with the current best limit orders and no price is submitted. Thus, the price setting issue for intermittent generators can be solved by this suggestion.

5.6.2 Model conventional producers' and consumers' entrance into the intraday market

As mentioned in Section 5.6.1, intermittent producers can just submit market orders. Therefore, before their first entrance there must be other agents like non-dispatched generators and unsatisfied consumers in the day-ahead market that are flexible enough to participate in the intraday market with limit orders. The method suggested by Von Selasinsky (2016) calculates the optimal offer prices based on the trade-off between profit and risk for conventional power plants, as well as elastic consumers. Even though he did not model the order arrivals by stochastic processes, for price-setting decisions he utilizes all available information from the open order book to model the success of trade probability.

5.7 Conclusion

The simulation of the continuous trading intraday market (limit order book) could help to analyze different characterisitics of this market. For example, it can help market participants to test their trading strategies with different risk preferences to compare their performance with volume weighted average price and adopt their optimal level of risk and therefore maximize their expected profit. It also helps market participants, especially the flexible producers, to test their automated trading strategy softwares and check their arbitrage opportunities that may arise in the limit order book.

Moreover, it is helpful for market designers and regulators to measure the usefulness of the market with market depth which is the quantity of electricity that is offered at certain prices at given times. The higher is the market depth, the more of the available flexibility is directly offered to the market and the more likely it is that renewables decide to balance their forecast errors in the intraday market. By having access to a market simulator, market designers can also measure market liquidity which is the volume of transactions in the market. By assuming the other factors equal, the higher market liquidity increases the possibility of finding a trading partner. It is also possible to test various congestion management techniques.

The fundamental basis for simulating the limit order book suggested in this paper combined with ideas mentioned in Garnier and Madlener (2015) and Von Selasinsky (2016) can lead us towards a full simulation of continuous trading intraday market in a more realistic context.

Bibliography

Abrell, J. and Kunz, F. (2015). Integrating intermittent renewable wind generation-a stochastic multi-market electricity model for the european electricity market. *Networks and Spatial Economics*, 15(1):117–147.

ACER, (2019). Establishing a single methodology for pricing intraday cross-zonal capacity. Available at :`https://www.acer.europa.eu/Official_documents/Acts_of_the_Agency/Individual%20decisions/ACER%20Decision%2001-2019%20on%20intraday%20cross-zonal%20capacity%20pricing%20methodology.pdf`. (accessed 10.08.2019).

Aravena, I. and Papavasiliou, A. (2017). Renewable energy integration in zonal markets. *IEEE Transactions on Power Systems*, 32(2):1334–1349.

Birge, J. and Mulvey, J. (1996). Stochastic programming. In Avriel, M. and Golany, B., editors, *Mathematical programming for industrial engineers*, page 543–574. Marcel Dekker, New York.

Bjorndal, E., Bjorndal, M., Midthun, K., and Tomasgard, A. (2018). Stochastic electricity dispatch: A challenge for market design. *Energy*, 150:992–1005.

Bjorndal, E., Bjorndal, M., Midthun, K. T., and Zakeri, G. (2016). Congestion management in a stochastic dispatch model for electricity markets. Discussion paper, no. 2016/12, NHH Dept. of Business and Management Science. Available at SSRN: https://ssrn.com/abstract=2829365.

Bjørndal, M. (2000). Topics on electricity transmission pricing. Phd thesis, Norwegian School of Economics (NHH.

Bjørndal, M. and Jørnsten, K. (2001). Zonal pricing in a deregulated electricity market. *The Energy Journal*, pages 51–73.

Bjørndal, M. and Jörnsten, K. (2007). Benefits from coordinating congestion management—the nordic power market. *Energy policy*, 35(3):1978–1991.

Bjørndal, M., Jørnsten, K., and Pignon, V. (2003). Congestion management in the nordic power market—counter purchases and zonal pricing. *Competition and Regulation in Network Industries*, 4(3):271–292.

Bjørndal, M., Jörnsten, K., and Rud, L. (2010). Capacity charges: A price adjustment process for managing congestion in electricity transmission networks. In *Energy, Natural Resources and Environmental Economics*, pages 267–292. Springer.

Borenstein, S. (2002). The trouble with electricity markets: understanding california's restructuring disaster. *Journal of economic perspectives*, 16(1):191–211.

Borggrefe, F. and Neuhoff, K. (2011). Balancing and intraday market design: Options for wind integration. Discussion paper 1162, DIW Berlin.

Boukas, I., Ernst, D., Papavasiliou, A., and Cornélusse, B. (2018). Intra-day bidding strategies for storage devices using deep reinforcement learning. In *International Conference on the European Energy Market*, page 6. IEEE.

Braun, S. (2016). Hydropower storage optimization considering spot and intraday auction market. *Energy Procedia*, 87:36–44.

Braun, S. and Hoffmann, R. (2016). Intraday optimization of pumped hydro power plants in the german electricity market. *Energy Procedia*, 87:45–52.

Brunekreeft, G., Neuhoff, K., and Newbery, D. (2005). Electricity transmission: An overview of the current debate. *Utilities Policy*, 13(2):73–93.

Budish, E., Cramton, P., and Shim, J. (2014). Implementation details for frequent batch auctions: Slowing down markets to the blink of an eye. *American Economic Review*, 104(5):418–24.

Budish, E., Cramton, P., and Shim, J. (2015). The high-frequency trading arms race: Frequent batch auctions as a market design response. *The Quarterly Journal of Economics*, 130(4):1547–1621.

Canestrelli, E. and Giove, S. (1999). Scenarios identification for financial modelling. In canestrelli, E., editor, *Current Topics in Quantitative Finance*, pages 25–36. Springer, Berlin Heidelberg GmbH.

Chao, H.-P. and Peck, S. (1996). A market mechanism for electric power transmission. *Journal of regulatory economics*, 10(1):25–59.

Chaves-Ávila, J. and Fernandes, C. (2015). The spanish intraday market design: A successful solution to balance renewable generation? *Renewable Energy*, 74:422–432.

Commission Regulation (EU), (2015). Establishing a guideline on capacity allocation and congestion management. Available at :`http://data.europa.eu/eli/reg/2015/1222/oj`. (accessed 14.08.2019).

Cramton, P. (2017). Electricity market design. *Oxford Review of Economic Policy*, 33(4):589–612.

Dierstein, C. (2017). Impact of generation shift key determination on flow based market coupling. In *14th International Conference on the European Energy Market (EEM)*, pages 1–7. IEEE.

Dijk, J. and Willems, B. (2011). The effect of counter-trading on competition in electricity markets. *Energy Policy*, 39(3):1764–1773.

Du, C., Wang, X., Wang, X., Shao, C., and Xiao, Y. (2018). A mechanism of intraday market design for promoting wind power integration. *CSEE Journal of Power and Energy Systems*, 4(3):293–298.

Dupačová, J., Consigli, G., and Wallace, S. W. (2000). Scenarios for multistage stochastic programs. *Annals of operations research*, 100:25–53.

Engmark, E., Sandven, H., Fleten, S.-E., and Klæboe, G. (2017). Stochastic multistage bidding optimisation for a nordic hydro power producer in the post-spot markets. Master thesis, Norwegian University of Science and Technology (NTNU).

Engmark, E., Sandven, H., Fleten, S.-E., and Klæboe, G. (2018). Stochastic multistage bidding optimisation in an intraday market with limited liquidity. In *2018 15th International Conference on the European Energy Market (EEM)*, pages 1–5. IEEE.

EPEX-SPOT (2017). *Price Coupling of Regions*. `http://www.epexspot.com/en/market-coupling/`. Online; accessed 30 October 2017.

Fabbri, A., Roman, T., Abbad, J., and Quezada, V. (2005). Assessment of the cost associated with wind generation prediction errors in a liberalized electricity market. *IEEE Transactions on Power Systems*, 20(3):1440–1446.

Garnier, E. and Madlener, R. (2015). Balancing forecast errors in continuous-trade intraday markets. *Energy Systems*, 6(3):361–388.

Goldthau, A. (2016). *The handbook of global energy policy*. John Wiley & Sons.

Graeber, D., Semmig, A., Kleine, A., and Weber, A. (2010). RES-E integration in Germany using the example of EnBW TSO. In *2010 7th International Conference on the European Energy Market*, pages 1–7. IEEE.

Gürtler, M. and Paulsen, T. (2018). The effect of wind and solar power forecasts on day-ahead and intraday electricity prices in germany. *Energy Economics*, 75:150–162.

Hagemann, S. (2013a). Price determinants in the german intraday market for electricity: an empirical analysis. EWL working paper 18/2013, University of Duisburg-Essen.

Hagemann, S. (2013b). Price determinants in the german intraday market for electricity: an empirical analysis. Technical report, EWL working paper.

Harvey, S. M. and Hogan, W. W. (2000). Nodal and zonal congestion management and the exercise of market power. Working paper, Harvard University.

Henriot, A. (2012a). Market design with wind: managing low-predictability in intraday markets. RSCAS Working Papers 2012/63, European University Institute.

Henriot, A. (2012b). Market design with wind: managing low-predictability in intraday markets. *EUI working papers RSCAS 2012/63*.

Hentschel, J., Spliethoff, H., et al. (2016). A parametric approach for the valuation of power plant flexibility options. *Energy Reports*, 2:40–47.

Hers, J., Ozdemir, O., Kolokathis, C., and Nieuwenhout, F. (2009). Net benefits of a new dutch congestion management system. Working paper, ECN.

Hobbs, B. F., Rijkers, F. A., and Boots, M. G. (2005). The more cooperation, the more competition? a cournot analysis of the benefits of electric market coupling. *The Energy Journal*, pages 69–97.

Hogan, W. and Newton, M. (2001). Electricity market power mitigation. `http://www.raabassociates.org/Articles/Roundtable_Hogan051801.pdf`. Online; accessed 30 October 2017.

Hogan, W. W. (1999). Transmission congestion: the nodal-zonal debate revisited. Working paper 29, Harvard University, John F. Kennedy School of Government, Center for Business and Government.

Holmberg, P., Lazarczyk, E., et al. (2015). Comparison of congestion management techniques: Nodal, zonal and discriminatory pricing. *Energy Journal*, 36(2):145–166.

Jafari, A. M., Zareipour, H., Schellenberg, A., and Amjady, N. (2014). The value of intra-day markets in power systems with high wind power penetration. *IEEE Transactions on Power Systems*, 29(3):1121–1132.

Jegleim, B. (2015). Flow based market coupling. Master's thesis, NTNU.

Jensen, T. V., Kazempour, J., and Pinson, P. (2017). Cost-optimal ATCs in zonal electricity markets. *IEEE Transactions on Power Systems*, 33(4):3624–3633.

Karanfil, F. and Li, Y. (2015). Wind up with continuous intra-day electricity markets? the integration of large-share wind power generation in denmark. Working paper INIS-FR–17-0766.

Kiesel, R. and Luckner, N. G. V. (2018). Time-varying market order arrival rates and their impact on optimal intraday trading. `http://www.thematicsemester.com/wp-content/uploads/2018/03/paris2018-hawkes.pdf`. University of Duisburg-Essen.

Kiesel, R. and Paraschiv, F. (2017). Econometric analysis of 15-minute intraday electricity prices. *Energy Economics*, 64:77–90.

Kleit, A. N., Wood III, P., Brennan, T. J., Considine, T. J., Daniel, T., and more, . (2006). *Electric Choices: Deregulation and the Future of Electric Power*. Rowman & Littlefield Publishers.

Kolberg, J. K. and Waage, K. (2018). Artificial intelligence and nord pool's intraday electricity market elbas: a demonstration and pragmatic evaluation of employing deep learning for price prediction: using extensive market data and spatio-temporal weather forecasts. Master thesis, Norwegian School of Economics (NHH).

Kunz, F. (2013). Improving congestion management: how to facilitate the integration of renewable generation in germany. *The Energy Journal*, 34(4):55–79.

Löhndorf, N., Wozabal, D., and Minner, S. (2013). Optimizing trading decisions for hydro storage systems using approximate dual dynamic programming. *Operations Research*, 61(4):810–823.

Luckock, H. et al. (2003). A steady-state model of the continuous double auction. *Quantitative Finance*, 3(5):385–404.

Mauritzen, J. (2015). Now or later? trading wind power closer to real time and how poorly designed subsidies lead to higher balancing costs. *The Energy Journal*, 36(4).

Meeus, L., Vandezande, L., Cole, S., and Belmans, R. (2009). Market coupling and the importance of price coordination between power exchanges. *Energy*, 34(3):228–234.

Monteiro, C., Bessa, R., Miranda, V., Botterud, A., Wang, J., and Conzelmann, G. (2009). Wind power forecasting: State-of-the-art 2009, Argonne National Laboratory. *Decision and Information Sciences Division, report ANL/DIS-10-1, Lemont, Illinois, USA, doi*, 10:968212.

Monteiro, C., Ramirez-Rosado, I., Fernandez-Jimenez, L., and Conde, P. (2016). Short-term price forecasting models based on artificial neural networks for intraday sessions in the iberian electricity market. *Energies*, 9(9):721.

Morales, J. M., Zugno, M., Pineda, S., and Pinson, P. (2014). Electricity market clearing with improved scheduling of stochastic production. *European Journal of Operational Research*, 235(3):765–774.

NETL (2012). Impact of load following on power plant cost and performance. Technical report DOE/NETL-2013/1592, National Energy Technology Laboratory.

Neuhoff, K. and Boyd, R. (2011). International experiences of nodal pricing implementation. Working document, Berlin: Climate Policy Initiative.

Neuhoff, K., Richstein, J., and May, N. (2016a). Auctions for intraday-trading impacts on efficient power markets and secure system operation. Research report, DIW Berlin.

Neuhoff, K., Ritter, N., Salah-Abou-El-Enien, A., and Vassilopoulos, P. (2016b). Intraday markets for power: Discretizing the continuous trading? Technical report, E.

Neuhoff, K., Ritter, N., Salah-Abou-El-Enien, A., and Vassilopoulos, P. (2016c). Intraday markets for power: Discretizing the continuous trading? Working Paper EPRG 1609/Cambridge WP in Economics 1616, Energy Policy Research Group and University of Cambridge.

NordPool (2016a). Cross-border intraday market project (xbid). `https://www.nordpoolspot.com/globalassets/downloadcenter/xbid/xbid-qa_final.pdf`. Online; accessed 18.11.2019.

NordPool (2016b). Nord pool intraday user guide. `https://www.nordpoolspot.com/globalassets/download-center/intraday/intraday-user-guide.pdf`. Online; accessed 18.11.2019.

NREL (2012). Wind power forecasting error distributions: An international comparison. In *11th annual international workshop on large-scale integration of wind power into power systems*, Lisbon, Portugal.

NVE THEMA Consulting Group (2019). Effects of a more intraday-driven market. Ekstern rapport Nr 2/2019.

Oggioni, G. and Smeers, Y. (2012). Degrees of coordination in market coupling and counter-trading. *The Energy Journal*, 33(3):39–90.

Oggioni, G. and Smeers, Y. (2013). Market failures of market coupling and counter-trading in europe: An illustrative model based discussion. *Energy Economics*, 35:74–87.

Oggioni, G., Smeers, Y., Allevi, E., and Schaible, S. (2012). A generalized nash equilibrium model of market coupling in the european power system. *Networks and Spatial Economics*, 12(4):503–560.

Palchak, D. and Denholm, P. (2014). Impact of generator flexibility on electric system costs and integration of renewable energy. Technical report, National Renewable Energy Laboratory (NREL).

Panagiotelis, A. and Smith, M. (2008). Bayesian density forecasting of intraday electricity prices using multivariate skew t distributions. *International Journal of Forecasting*, 24(4):710–727.

Pape, C., Hagemann, S., and Weber, C. (2016). Are fundamentals enough? explaining price variations in the german day-ahead and intraday power market. *Energy Economics*, 54:376–387.

PCR (2013). Euphemia public description. PCR market coupling algorithm. Technical report, EPEX Spot–APX–Belpex–Nord Pool Spot–OMIE–Mercatoelettrico (GME)–OTE.

Pillay, A., Karthikeyan, S. P., and Kothari, D. (2015). Congestion management in power systems – a review. *International Journal of Electrical Power and Energy Systems*, 70:83–90.

Pinson, P., Madsen, H., Nielsen, H. A., Papaefthymiou, G., and Klöckl, B. (2009). From probabilistic forecasts to statistical scenarios of short-term wind power production. *Wind Energy: An International Journal for Progress and Applications in Wind Power Conversion Technology*, 12:51–62.

Pritchard, G. (2011). Short-term variations in wind power: Some quantile-type models for probabilistic forecasting. *Wind Energy*, 14:255–269.

Qin, J., Rajagopal, R., and Varaiya, P. P. (2017). Flexible market for smart grid: coordinated trading of contingent contracts. *IEEE Transactions on Control of Network Systems*.

Rahimi, S., Bjorndal, M., Bjorndal, E., and Andersson, J. (2018). Congestion management in continuous trading intraday market. *CMS 2018 - Conference on Computational Management Science*.

Rahman, A. (2011). An ex ante probabilistic study of market power with emphasis on the transmission constraints. Master thesis, Royal Institute of Technology (KTH).

Rious, V., Usaola, J., Saguan, M., Glachant, J.-M., and Dessante, P. (2008). Assessing available transfer capacity on a realistic european network: impact of assumptions on wind power generation. In *First international conference on infrastructure systems and services: Building networks for a brighter future*, pages 1–6. IEEE.

Scharff, R. and Amelin, M. (2016). Trading behaviour on the continuous intraday market elbas. *Energy Policy*, 88:544–557.

Schroder, S. T. and Weber, A. (2011). Optimal power market timing for wind energy. In *EWEA Annual Event 2011*. European Wind Energy Association (EWEA).

Schweppe, F. C., Caramanis, M. C., Tabors, R. D., and Bohn, R. E. (1988). *Spot pricing of electricity*. Springer Science & Business Media.

Sekamane, J. K. (2018). Reanalysing price asymmetries in the nordic intraday market. In *2018 15th International Conference on the European Energy Market (EEM)*, pages 1–5. IEEE.

Singh, H. (1999). Market power mitigation in electricity markets. In *IEEE Tutorial on Game Theory Applications in Electric Power Markets*, pages 70–77. IEEE.

Skajaa, A., Edlund, K., and Morales, J. M. (2015). Intraday trading of wind energy. *IEEE Transactions on Power Systems*, 30(6):3181–3189.

Song, Y.-H. (2003). *Operation of market-oriented power systems*. Springer Science & Business Media.

Soysal, E. R., Olsen, O. J., Skytte, K., and Sekamane, J. K. (2017). Intraday market asymmetries—a nordic example. In *2017 14th International Conference on the European Energy Market (EEM)*, pages 1–6. IEEE.

Statnett, FINDRID, S.-E. (2016). methodology and concepts for the nordic flow based market coupling approach. Technical report. Working paper.

Usaola, J. and Moreno, M. A. (2009). Optimal bidding of wind energy in intraday markets. In *6th International Conference on the European Energy Market*, pages 1–7. IEEE.

van Blijswijk, M. J. and de Vries, L. J. (2012). Evaluating congestion management in the dutch electricity transmission grid. *Energy policy*, 51:916–926.

Van den Bergh, K., Boury, J., and Delarue, E. (2016). The flow-based market coupling in central western europe: Concepts and definitions. *The Electricity Journal*, 29(1):24–29.

Vardanyan, Y. and Hesamzadeh, M. R. (2017). The coordinated bidding of a hydropower producer in three-settlement markets with time-dependent risk measure. *Electric Power Systems Research*, 151:40–58.

Verseille, J. and Alaimo, S. (2018). Cross border intraday (xbid) trading solution pre-launch event. https://www.nordpoolgroup.com/globalassets/download-center/xbid/180131_xbid-presentation-go-live-launch-event.pdf. Online; accessed 06.01.2020.

Von Selasinsky, A. (2016). *The integration of renewable energy sources in continuous intraday markets for electricity*. Phd thesis, Technical University of Dresden.

Vries, L. J. D. and Hakvoort, R. A. (2002). An economic assessment of congestion management methods for electricity transmission networks. *Competition and Regulation in Network Industries*, 3(4):425–466.

Weber, A. and Schröder, S. (2011). Efficiency of continuous double auctions in the electricity market. In *Energy Market (EEM), 2011 8th International Conference on the European*, pages 87–92. IEEE.

Weber, C. (2010). Adequate intraday market design to enable the integration of wind energy into the european power systems. *Energy Policy*, 38(7):3155–3163.

WindEurope (2017). Wind in power. http://windeurope.org/wp-content/uploads/files/about-wind/statistics/WindEurope-Annual-Statistics-2017.pdf. Online; accessed 18.11.2019.

WindEurope (2019). Wind energy in europe in 2018. https://windeurope.org/wp-content/uploads/files/about-wind/statistics/WindEurope-Annual-Statistics-2018.pdf. (accessed 18.09.2019).

Wu, F. F. and Varaiya, P. (1999). Coordinated multilateral trades for electric power networks: theory and implementation. *International Journal of Electrical Power & Energy Systems*, 21(2):75–102.

Ziel, F. (2017). Modeling the impact of wind and solar power forecasting errors on intraday electricity prices. In *2017 14th International Conference on the European Energy Market (EEM)*, pages 1–5. IEEE.