

University of Pavia

Behavior of electrical market operators bidding into the intraday electricity market

PhD thesis

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Abstract

This research encompasses an extensive investigation into the Single European Intraday Market Coupling (SIDC), which is the design target model adopted by the European authorities, with a particular focus on its implementation within the Italian context. SIDC operates on a continuous energy trading mechanism, wherein the allocation of available interconnection capacity among bidding zones is implicitly determined. This study commences with a concise overview, followed by a comprehensive exposition of the fundamental attributes and prospective advancements within the SIDC framework. In addition to these foundational aspects, the work incorporates a meticulous examination of statistical analyses conducted on transactional data from the year 2020, derived from the Iberian, the German and the French SIDC markets. Furthermore, the study encompasses the outcomes of diverse simulations specifically designed to elucidate the intricacies of the continuous trading mechanism. This multifaceted research endeavor contributes to a deeper comprehension of SIDC and its implications, furnishing valuable insights into its operational dynamics and potential avenues for further refinement and optimization. An analysis between two iterations of the Italian intra-day market, namely, the version preceding and succeeding the incorporation of the Single Intraday Market Coupling (SIDC) framework is also carried out. This comparative analysis encompasses an examination of traded volumes across various market sessions, an assessment of price trends and volatility in relation to submitted orders (while also considering day-ahead market prices), and an investigation into the submission frequency of orders during continuous trading sessions. A particular emphasis is placed on orders submitted for distinct generation technologies. Subsequently, the report proceeds to provide an overview of economic models equipped to characterize the dynamics of continuous trading markets. This includes an exploration of optimization, equilibrium, and simulation models. Special attention is accorded to game theory techniques, which illumi-

nate the strategies that market participants may employ to maximize their profits or establish cooperative equilibria. A more comprehensive analysis delves into simulation models, which are deemed especially suited for application in intra-day continuous trading electricity markets. The report outlines prominent algorithms employed in simulating market player strategies, with a focus on their profit-maximizing approaches, informed by market data, external events, or historical data at their disposal. Of particular significance is the examination of the adaptive-aggressiveness model developed by Vytellingum, which characterizes the propensity of agents to engage actively in the market based on the information they acquire during trading sessions. In its final segment, the report introduces two innovative models tailored for simulating continuous trading electricity markets. The first model builds upon the adaptive-aggressiveness framework, employing a genetic algorithm to iteratively optimize the key parameter proposed by Vytellingum. The primary objective is to enhance both social welfare and the volume of exchanged energy. The second model, conversely, endeavors to faithfully replicate the distinctive facets of continuous trading markets. These facets encompass market efficiency, price trends contingent upon internal and external factors, and the frequency of order submissions by market participants. Subsequently, both models are applied to test cases, with the ensuing results presented and scrutinized.

Chapter 1

Introduction

1.1 Background and problem statement

The intra-day electricity markets (IDMs) emerged with the liberalization of the electricity market [1]. They enable energy traders to exchange electricity throughout the day and are typically used to make adjustments to schedules established at the closure of the Day-Ahead Market (DAM) [2]. In Europe, these markets are structured with both auction-based and continuous trading mechanisms [3]. With the auction mechanism, market participants submit bids within a specified time frame [4], after which all buy and sell offers are ordered, with buy offers sorted by increasing prices and sell offers sorted by decreasing prices. These orderings form the supply and demand curves, and when intersected, determine the energy price. On the other hand, continuous trading involves instantaneous pairing of buy and sell offers when specific conditions are met [5].

The recent acceleration of the decarbonization process in the energy system, promoting the integration of renewable energy generation, has increased the utilization of these markets [6]. Production schedules for intermittent sources like solar and wind require adjustments closer to the delivery time to account for the latest production forecasts [7]. At the European level, it was decided to implement an intra-day market with continuous trading, allowing energy traders to exchange electricity up to one hour before delivery. This mechanism was introduced in 2018 by the initial 15 countries that launched the Single Intraday Market Coupling (SIDC) project [8]. Subsequently, Italy also joined this market in September 2021 [9].

Numerous studies in the literature report the enhanced efficiency, in terms of liquidity and volatility, of a hybrid market combining continuous trading and auctions, exemplified by SIDC, compared to markets solely relying on auctions or continuous trading [10]. Furthermore, there is evidence of reduced imbalances in non-programmable renewable sources due to the market's alignment with real-time conditions [11]. Additionally, [12] provides examples of how continuous trading empowers market participants to adopt various strategies based on their unique characteristics, such as their energy generation technology, market information, and external factors like weather updates.

As a result, there is a growing need to develop models capable of simulating the dynamics of continuous trading markets, recreating various recurrent trading scenarios, and ultimately optimizing their performance.

The objective of the research activities described in this report is twofold : first it is to investigate the functioning of the SIDC and its continuous trading, as well as to analyze some European intra-day markets, such as the Iberian, the German, the French and the Italian markets, which currently feature national auctions, rather than pan-European ones, integrated with continuous trading. Second, it is to construct models that can faithfully simulate the behavior of continuous trading, with a focus on understanding which parameters can maximize system welfare efficiency.

1.2 Objective of the study

The objective of this study can be divided into three main components. Firstly, we aim to provide a comprehensive overview of the recently established European single intraday market coupling, with a particular emphasis on its implications within the Italian market context. Secondly, we intend to elucidate the operational intricacies of the largest European intraday markets. This will be accomplished through an array of statistical analyses conducted on historical data sourced from the NEMO (Nominated Electricity Market Operator) of key European regions, including the Iberian, German, French, and Italian markets. These analyses will yield valuable insights into the historical performance and dynamics of these markets. Lastly, the study seeks to develop and optimize models capable of accurately replicating the contin-

uous trading mechanisms within the European intraday market. These models will consider and incorporate all relevant aspects and factors associated with the real-world complexities of the European intraday market, enabling us to better understand and potentially enhance its functioning.

1.3 Methodology

To achieve our research objectives, we embarked on a comprehensive analysis of various European intraday markets by extensively consulting the websites of Nominated Electricity Market Operators (NEMOs). Our examination encompassed a wide array of key parameters governing these markets [13], including trends in prices and order volumes, probability density analyses of orders submitted across different time-frames, correlation analyses linking day-ahead prices to continuous trading prices throughout each hour of the day, time series analyses tracking price behaviors as delivery time approached, as well as regression and cluster analyses. Our initial focus was to elucidate the distinctive characteristics of each European market individually. This approach allowed us to discern how the interplay between auctions and continuous trading, a pivotal aspect of market design [3], impacted market outcomes. Subsequently, we aimed to provide overarching insights into continuous trading, offering a strategic framework that market participants could adopt to navigate the continuous energy trading landscape effectively and secure profitable outcomes. Having gained a thorough understanding of intraday market dynamics, we proceeded to explore various economic models applicable to the energy sector, with a specific emphasis on developing models capable of replicating continuous trading dynamics. While briefly introducing equilibrium models like Bertrand [14], Cournot [15], conjectural variation [16], and supply function criteria [17], we identified agent-based simulation models as the most suitable for our purposes [18]. Among these models, the Vitellingum strategy [19] stood out as one of the most effective in replicating market conditions. Our research then involved the creation of two distinct agent-based models. In the first model, we leveraged genetic algorithms, specifically NSGA-II, to optimize agent strategies. This optimization aimed to enhance the overall welfare of the system while minimizing the quantity of energy not exchanged, which could result in penalties for imbalances. In the second model, we devised various strategies

based on each player's unique technological capabilities. We also developed an algorithm to capture the trend in order submissions, noting a significant surge in submissions during the final hour of the market. Additionally, we incorporated external factors, such as wind energy predictions, into our model to account for the market's increasing dependence on intermittent energy resources. This multifaceted approach enabled us to construct robust models that could faithfully replicate the evolving dynamics of the continuously trading energy market.

1.4 Achievements and contributions

The accomplishments of this research work encompass the following key achievements:

- **Comprehensive Examination of the European Single Intraday Market:** This study offers an intricate and precise analysis of the newly established Single Intraday Market in Europe, with a particular focus on distinguishing the diverse market designs adopted by European countries. This overview has been reported in a deliverable of the national research center (RSE) [20].
- **In-Depth Exploration of the Italian Context:** The research delves into the specific nuances of the Italian energy market, providing a comparative analysis of the previous auction-based model against the current hybrid model. This study has been published in a deliverable of the national research center [21] and in the paper [22].
- **Statistical Analysis of Intraday Market Dynamics:** Through rigorous statistical analyses of extensive data sets sourced from prominent Nominated Electricity Market Operators (NEMOs) across European nations, this study elucidates crucial aspects of the intraday market. These analyses serve as a foundation for the development of a novel trading strategy intended to guide market operators in their continuous trading endeavors. These analyses has been published in several articles: [23], [24], [25] and [26]
- **Genetic Algorithm Optimization:** The research integrates genetic algorithms to optimize continuous trading strategies employed by different market participants. This optimization process is aimed at enhancing overall market welfare while simultaneously mitigating

imbalances. This work it is still under review and it can be found in [27]

- **Agent-Based Model Creation:** A sophisticated agent-based model has been formulated to accurately replicate pivotal market characteristics. This model captures essential features such as order density across different timeframes, price formulation influenced by diverse technologies participating in the market, and price trends driven by external information, including weather forecasts. This work is still under review in [28]

1.5 Outline of the thesis

The thesis is organized into several chapters, each contributing to a comprehensive exploration of the subject matter. In Chapter Two, we delve into the European intraday energy market, specifically focusing on the Single Intraday Market Coupling (SIDC). This section provides a foundational understanding of the market's structure and operation. Chapter three presents a series of rigorous statistical analyses conducted on the Iberian, German, and French intraday energy markets. These analyses offer valuable insights into market dynamics, trends, and performance metrics, enhancing our understanding of how these markets function. Chapter four takes an in-depth look at the Italian energy market, examining its unique context and characteristics. Within this chapter, we perform statistical analyses to compare the Italian intraday market before and after the introduction of SIDC. This analysis provides valuable insights into the market's evolution. Chapter five explores the historical landscape of energy continuous trading market models. It delves into the models that have been studied and utilized in the past, providing a comprehensive overview of their development and relevance in understanding market dynamics. Chapter six highlights two innovative energy market models created specifically to study and optimize continuous energy trading. These models represent cutting-edge approaches aimed at enhancing our understanding of market dynamics and optimizing market performance. The final chapter summarizes the key findings and insights derived from the preceding chapters. It offers a comprehensive synthesis of the research outcomes, implications, and conclusions, providing a coherent and insightful conclusion to the thesis.

Chapter 2

Intraday Electricity Market

2.1 XBID platform and SIDC project

During 2012, the main European NEMO (Nominated Electricity Market Operators) together European TSO (Transmission System Operators) of 12 countries launched the 'XBID' platform [29]. It consisted in a common platform to exchange energy in continuous during the intraday market allowing an implicit allocation capacity [30]. The project started in 2018 under the name of 'Single Intraday Market Coupling' [31] aiming at creating a unique intraday market among all European countries in which agents can exchange energy continuously without any physical border excepted the capacity limits. Besides continuous trading, European countries inserted different number of auctions to find a solution able at improving the market liquidity and enhancing the interconnection capacity [32]. The first 'go-live' took place in June 2018 involving 15 countries, with the second one in November 2019 the project has been extend to other 7 countries, while the third wave in September 2021 involved the Italian bidding zones [24]. Through a centrally managed and supported information technology platform by Deutsche Börse [33], in the SIDC, market orders submitted by market operators, managed by any NEMO and from any European nation, are collected in a single centralized register called the Shared Order Book (SOB) [34]. Similarly, various TSOs make transit capacities available, which are collected and managed centrally by a dedicated module called the Capacity Management Module (CMM) [35]. With the information gathered in the order book and the updated transit capacities, a sell order and a buy order are matched together, regardless of the

originating nation or market area, if their respective bid prices are compatible and if there is sufficient physical transmission capacity in the underlying system to transfer the energy being traded [23]. If there is insufficient transmission capacity between two areas, the corresponding orders in the order book become invisible to each other, as they cannot be matched due to the lack of capacity. Therefore, an operator can only observe the orders from other market areas if they are actually reachable. In the SIDC, the matching of two orders is performed centrally only if the unit purchase price is greater than or equal to the selling price, and in the presence of multiple orders in the register with the same price, the first submitted order is selected for matching, according to a logic known as "first-come, first-served" [36].

2.2 European countries and respectively Nominated Electricity Market Operators

The participation of the European countries to the SIDC project is shown in 2.1 and in 2.2

First Go-Live in June 2018	Second Go-Live in November 2019
15 countries	7 countries
Austria	Bulgaria
Belgium	Croatia
Denmark	Czech-Republic
Estonia	Hungary
Finland	Poland
France	Romania
Germany	Slovenia
Latvia	
Lithuania	
Luxembourg	Third Go-Live in September 2021
Norway	Italy
The Netherlands	
Portugal	
Spain	
Sweden	

Figure 2.1: Go-live executed

Participation is carried out through Nominated Electricity Market Operators (NEMOs) [37], which can serve one or multiple nations under either monopolistic (as is the case for Bulgaria, Czech Republic, Greece, Hungary, Italy, Portugal, Romania, Slovakia, Spain) or competitive regimes (for the remaining nations). As shown in 2.1, the two NEMOs, "NORD POOL" and "EPEX Spot," operate in competition across a dozen nations.

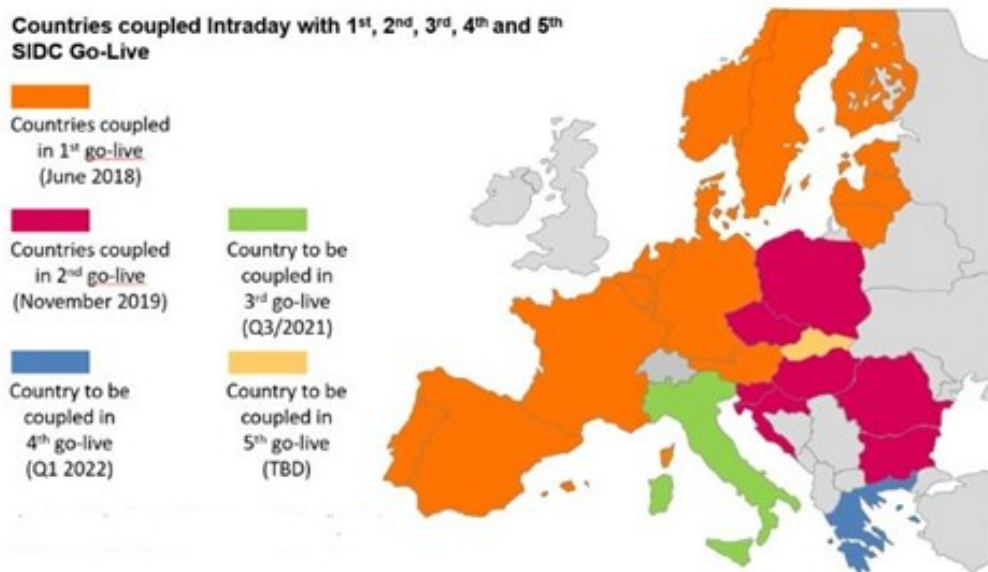


Figure 2.2: Go-live executed and planned

	Epex Spot	Nord Pool	Exaa AG	Ibex	Cropex	OTE	Nasdaq Oslo	Henex	Hupx	GME	Towarowa Gielda EnergySA	Omie	Opcom	Okte	BSP Energetska Borza
Austria	x	x	x												
Belgium	x	x													
Bulgaria				x											
Croatia					x										
Czech Republic						x									
Denmark	x	x													
Estonia		x													
Finland	x	x					x								
France	x	x													
Germany	x	x													
Greece								x							
Hungary									x						
Italy										x					
Latvia		x													
Lithuania		x													
Luxembourg	x	x													
Netherlands	x	x													
Poland	x	x									x				
Portugal															
Romania												x			
Slovakia													x		
Slovenia														x	
Spain												x			
Sweden	x	x													
England	x	x													

Table 2.1: Countries with the respective NEMO

The operator "NORD POOL" is primarily active in the Nordic and Baltic countries, namely Norway, Sweden, Finland, Denmark, Lithuania, Estonia, and Latvia. However, it also serves to a lesser extent the countries of Western and Central Europe, including Austria, Belgium, France, Germany, the Netherlands, and Poland. In recent years, NORD POOL has experienced a doubling of its intraday market volumes, increasing from 8.2 TWh in 2018 to 15.8 TWh in 2019. It has achieved access to more than half of the trades through API integration [38]. The operator "EPEX Spot" operates in Austria, Belgium, Denmark, Finland, France, Germany, England, Luxembourg, the Netherlands, Norway, Sweden, and Switzerland. Similarly, EPEX Spot has witnessed a significant increase in the volumes of energy traded in the intraday market, with a 21 % growth in traded energy from 2019 to 2020 [38]. Table 2.2 presents the volumes of trades conducted by the three major NEMOs in the intraday market during the year 2020.

SIDC NEMO	Volumes (TWh)
Epex Spot	111
Nord Pool	26
Omie	37

Table 2.2: Volumes exchanged by the principal NEMO

We would like to emphasize the role of GME (Gestore dei Mercati Energetici) among the Nominated Electricity Market Operators (NEMOs) involved in the SIDC project since its inception, even though Italy joined this market only in September 2021. In the year 2020, the volumes of energy traded in the Italian intraday market were estimated at approximately 25 TWh [39].

2.3 Bidding zones and zonal transmission capacity

The operation of the SIDC relies on the network being divided into different market zones ("bidding zones") and the definition of transmission capacities between these zones ("available transfer capacity") [40]. The identification of market zones is conducted and periodically reassessed based on congestion frequency and criteria such as efficiency [41]. There are two possible methods for identifying market zones [42]:

- "Expert-based" approach: This approach involves selecting configurations defined ex-ante through the merging or splitting of existing zones. These configurations are determined by Transmission System Operators (TSOs) based on their experience and quantitative analysis, hence the term "expert-based" identification.
- "Model-based" approach: This approach begins with an initial market simulation using nodal representation (calculating locational marginal prices, i.e., nodal prices) and subsequently aggregates nodes characterized by similar nodal prices to form market zones.

The task of calculating available capacity is assigned to the respective TSOs, who, in accordance with Article 2 of the CACM (Capacity Allocation and Congestion Management) regulation, delineate Capacity Calculation Regions (CCRs). These CCRs represent geographic areas where inter-zonal capacity calculations are applied [43] (2.3). The CRRs "IU" and "Channel" specifically connect Great Britain with Europe.

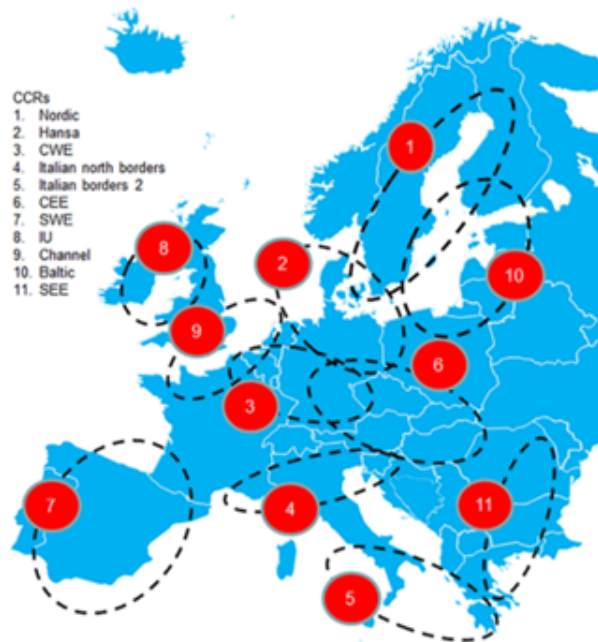


Figure 2.3: European CCR

Currently, the CACM (Capacity Allocation and Congestion Management) establishes two distinct methodologies applicable to capacity calculation: CNTC (Coordinated Net Transmission Capacity) and FB (Flow Based) [44]:

1. The Coordinated Net Transmission Capacity approach involves assessing and defining ex-ante the maximum allowable exchange of energy between adjacent market zones, taking

into account operational security constraints. The CACM suggests applying this method in regions where the inter-zonal capacities have little interdependence.

2. The flow-based approach, on the other hand, calculates energy exchanges between different zones based on Power Transfer Distribution Factors (PTDF) and limits them according to the available transmission margins on the most critical network elements (both intra-zonal and inter-zonal). These critical elements are those most at risk of being constrained due to security reasons (see, for example, Figure 2.4).

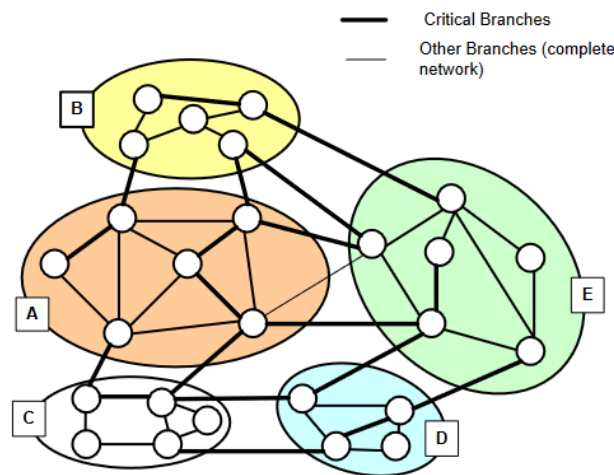


Figure 2.4: Market zones and critical branches

These methodologies enable the calculation of energy flows and constraints within the network, ensuring the reliable and secure operation of the interconnected market zones. The choice between CNTC and FB approaches depends on the level of interdependence between the inter-zonal capacities and the criticality of network elements in terms of security considerations.

Specifically, a Power Transfer Distribution Factor (PTDF) is a coefficient that defines the percentage by which an energy exchange between two hubs (e.g., between two market zones) flows through a specific network element [45]. The PTDF matrix associated with a particular network allows for the translation of the hypothesized commercial transaction between the two hubs into physical flows through various network elements.

It is evident that the flow-based method is more refined and precise than the CNTC method [46], allowing for a greater utilization of available transmission capacity by imposing fewer constraints compared to the CNTC method, which requires wider safety margins due to its

greater approximations.

For future developments, the CACM envisages that capacity calculations will be performed solely through the flow-based approach. The solution for available capacity is transmitted from the SIDC to the Local Trading Solution (LTS) of each NEMO in the form of a hub-to-hub matrix (H2H). The LTS serves as the interface between market participants and the SIDC, with participants only able to connect to the SIDC through the LTS of a specific NEMO [37]. Until the SIDC is capable of supporting inter-zonal capacity allocation based on the flow-based methodology, it is necessary to define the values of Available Transmission Capacity (ATC) for each inter-zonal border and make them available to the SIDC.

2.4 LIP - Local Implementation Project

The participation of various European countries in the SIDC is organized into distinct local implementation projects (17 to date), known as LIPs (Local Implementation Projects), each of which focuses on a predetermined subset of inter-zonal borders. A LIP consists of one or more Transmission System Operators (TSOs) or one or more Nominated Electricity Market Operators (NEMOs) with the objective of adapting local mechanisms to the SIDC platform, aligning ICT systems, and ensuring equal treatment among the various NEMOs. The local implementation project concerning Italy is LIP14 [23].

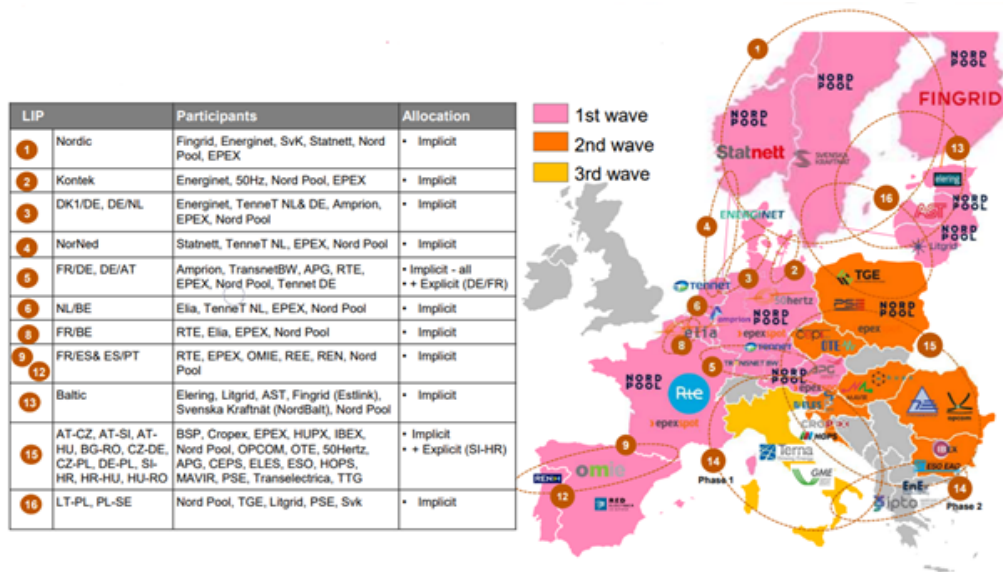


Figure 2.5: Local Implementation Projects

2.5 Volumes exchange and number of transactions

Since the launch of the SIDC, the volumes of energy traded in the intraday markets have experienced significant growth [47], surpassing the increase observed in the day-ahead market volumes. Table 2.3 provides an overview of the traded volumes by the main NEMOs participating in the SIDC market.

Table 2.3: Traded volumes by NEMOs (TWh)

	2018	2019	2020
EPEX	82	88	111
NORD POOL	8.2	15.8	26
OMIE	38	38	37

While EPEX and NORD POOL exhibit significant volume growth, OMIE’s volumes have remained relatively unchanged. This peculiarity in the Iberian intraday market can be attributed to its limited utilization, as continuous trading is punctuated by six auctions where energy is solely exchanged between Spain and Portugal [48]. Furthermore, the geographical position of the Iberian Peninsula hampers energy exchange with other European market zones due to the sole connection available with France.

Table 2.4 presents the traded volumes in 2019 and 2020 by the major countries participating in the SIDC [49].

Table 2.4: Traded volumes by countries (TWh)

Country	2019	2020
Austria	2.9	3.6
Belgium	1.8	2.8
France	7.7	10.7
England	21.7	23
Germany	53.8	63.6
Netherlands	3.3	4.3
Denmark, Sweden, Finland, and Norway	-	1.7
Switzerland	0.4	1.3

In Table 2.5, the numbers of transactions handled by the SIDC from mid-2018 to the end of 2021 are reported.

Table 2.5: Number of Transactions Managed by SIDC from Mid-2018 to End of 2021

Year	Period	Number of Transactions (millions)
2018	June-September	3.5
	October-December	4.3
2019	January-March	4.8
	April-June	5.8
	July-September	5.6
	October-December	7.2
2020	January-March	8.3
	April-June	9.3
	July-September	10.8
	October-December	11.9
2021	January-March	12.7
	April-June	14.9
	July-September	15.4

2.6 The main features of SIDC operation

This section describes the main features of SIDC operation, including the different platforms used for its proper functioning, the order matching algorithm in the continuous market, the role of auctions, the types of tradable products, and the various market time units (MTUs) which determine the market price at specific time periods.

2.7 The SOB, CMM, and SM modules

The mechanism of SIDC is defined by CACM and is based on three distinct modules: the Shared Order Book (SOB), the Capacity Management Module (CMM), and the Shipping Module (SM) [50]. The cooperation of these three modules enables continuous energy trading 24/7 between operators from different geographical areas, up to one hour before delivery. The SOB module encompasses the basic functionalities of continuous trading by managing the collection of orders submitted by operators from various market zones through their respective LTS [34]. It handles the placement of orders in the designated register (order book) based on the offered price and submission time, or matches orders in the case of fulfilled transactions. The SOB provides a continuous trading service, supporting different energy products such as hourly, half-hourly, quarter-hourly products, and block orders. The CMM module collects the available trans-

mission capacity between market zones and facilitates continuous allocation of cross-border capacity to all operators [36]. It interfaces with the various TSOs from different market zones, who continuously update the available transmission capacity following each completed transaction. It enables an implicit capacity allocation based on the operations conducted in the SOB module. The SM module provides the involved parties with information regarding their successfully concluded trades, enabling the actual energy exchanges for the corresponding financial transactions [37]. All orders from any represented market zone are stored in the order book if an immediate match is not found (except for the exceptions indicated in section...). The order book is centrally managed and visible to all operators. However, the interactions between the SOB and CMM modules offer operators different visibility of its content. As mentioned earlier, orders from market zones in regions where the transmission capacities defined by the CMM are saturated are invisible in the SOB. Refer to Figure 2.6, which illustrates the interactions between operators and the two main modules, SOB and CMM [9]:

1. An operator submits an order to their respective LTS.
2. The order is anonymized, and the LTS sends it to the SOB.
3. The SOB interfaces with the CMM, checks the transmission capacities, and determines the corresponding order visibility for each LTS.
4. The SOB provides feedback to the order submitter.
5. The SOB updates the order visibility for each LTS.
6. Each LTS only displays visible orders to the connected operators.

2.8 Market Time Unit

MTU refers to the Market Time Unit, which represents the temporal period for which the market price is established. It corresponds to the shortest common period between two bidding zones if they have different temporal definitions.

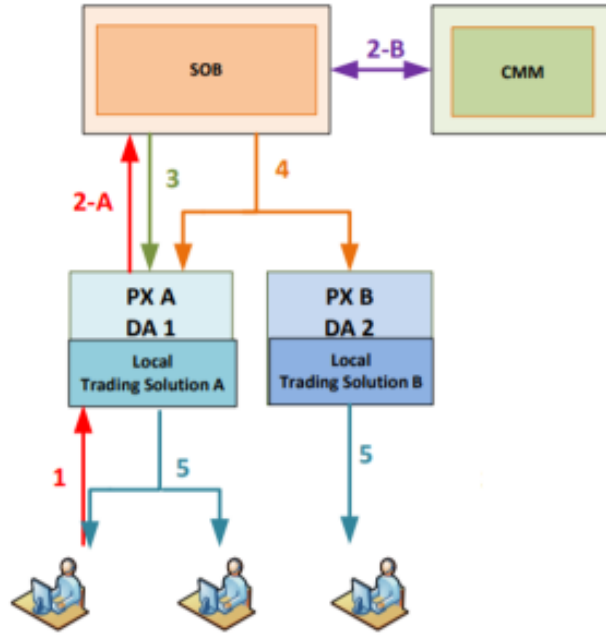


Figure 2.6: Interactions between market operators and SIDC modules

The current version of SIDC allows the matching of two orders only if both refer to the same MTU [51].

Each country defines the start and end times of the SIDC market at a specific hour. Table 2.6 shows these timings and the respective products with their corresponding MTUs. According to Article 59 of CACM, in the future, the opening of the SIDC market should occur one hour after the closure of the previous day's market for all participating nations. The closure should be determined at the regional level to maximize balancing opportunities for market participants and provide sufficient time for TSOs to carry out balancing activities and ensure network security.

Table 2.6: Gate opening and gate closing

	Austria	France	Germany	Iberian Peninsula	NL and BL	Nordic and Baltic	Bulgaria	Croatia	Czech Republic	Hungary	Poland	Romania	Slovenia	Italy
Open	All products	15:00	15:00	18:00	14:00	14:00	14:00	14:00	15:00	15:00	15:00	14:00	15:00	15:00
Close	15 min	h-30	h-30	h-5					h-60	h-60	h-60			
	30 min	h-30	h-30	h-5										
	hourly	h-30	h-30	h-30	h-60	h-5	h-60	h-60	h-30	h-5	h-60	h-60	h-60	h-60
	blocks	h-30	h-30	h-30	h-30	h-5	h-60	h-30	h-5	h-60	h-60	h-60	h-60	h-60

2.9 Orders characteristics

Every order submitted by a market operator is characterized by a specific contract associated with a production or consumption unit, or a portfolio [52]. Each contract must indicate the following:

- The order type, whether it is a sell or buy order.
- The product and its expiry, indicating whether it is an hourly, half-hourly, or quarter-hourly product and the hour range within which it can be matched. For example, "expiry 03" denotes an hourly product with delivery between 2 and 3 am.
- The quantity (MWh).
- The unit price (€/MWh).
- The delivery area.
- Any order restrictions (execution restrictions) that can be of different types:
 - NONE: The default condition, indicating that no restrictions apply to the order.
 - IOC (immediate-or-cancel): The order is canceled if it is not immediately matched (it never enters the order book).
 - FOK (fill-or-kill): The order is canceled if it is not fully matched (it never enters the order book).
 - AON (all-or-nothing): The order must be of block type and can only be matched with another single order of the same type for the entire quantity; otherwise, it enters the order book. Partial matches are not allowed.
- The validity restrictions of the order (validity restriction). These conditions include:
 - Good-for-session: Orders with this condition remain valid until the closure of the trading session (the default condition for orders).
 - Good-till-date: Orders with this condition are valid for a specific time period determined by the market operator who submitted the order.

In addition to the regular orders described above, there are three special types of orders [23]:

- ICE (iceberg): These orders keep the entire offered quantity concealed and gradually reveal only partial quantities after each match. Only the operator who submitted the order can see the total quantity.
- Iceberg with price increase: These orders are of the ICE type but with an automation applied to the price determination. Each time the visible portion is matched, the price of the subsequent portion will have a different price, calculated by applying a parameter called the "incremental price" (negative for purchases and positive for sales) to the previous value.
- Block: These orders (excluding ICE) encompass multiple contracts with the same product but with consecutive delivery periods.

2.10 Matching algorithm

The matching of orders is a deterministic process that signifies the completion of a negotiation [53]. A buy order and a sell order can only be matched if they belong to the same contract (product and MTU) and if the buy price is greater than or equal to the sell price. In the general case of orders without restrictions (NONE), the matched quantity is equal to the minimum quantity, and the order with the remaining quantity is placed in the order book. For orders with the FOK restriction, matching occurs only if there is no remaining quantity, while for orders with the IOC restriction, matching occurs only if an immediate counterparty is found. FOK and IOC orders are never entered into the order book.

The matching is based on a ranking that follows a merit order based on price and time. In the order book, sell orders are registered in ascending price order, and buy orders are registered in descending price order. This ensures that the first position for sell orders contains the order with the lowest sell price, and the first position for buy orders contains the order with the highest buy price, as illustrated in Figure 2.7:

At the same price, orders that entered first obtain a better position.

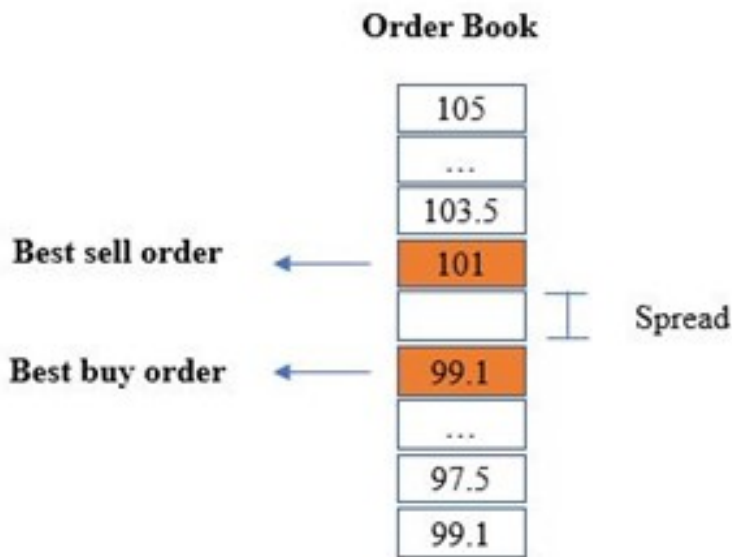


Figure 2.7: Orders Ranking

The verification of a match is triggered by the arrival of an order (new, modified, reactivated, or a new part of an ICE) to which a reception timestamp is assigned. If the price condition is not satisfied, the order is placed in the order book (if it has no restrictions). Conversely, it is matched with one or more orders already present in the order book, starting from the best position and scanning through the various positions as long as there is a quantity to be matched and as long as it encounters orders in those positions that satisfy the price condition. If it no longer finds orders that meet this condition and there is a remaining quantity, it is then placed in the order book (if it has no restrictions). The price of each match is always that of the order extracted from the order book, so the inserted order may receive multiple matches at different prices if it extracts multiple orders from the order book with different prices. This allows a buy order to complete the negotiation at a unit price lower than indicated, and a sell order at a higher price.

2.11 Auctions

As a market mechanism, SIDC adopts continuous trading but does not prevent the use of interleaved auctions alongside continuous trading [20]. In fact, some countries have already implemented inter-regional auctions (called CRIDA: complementary regional intraday auctions)

for the buying and selling of energy, while in the future, the introduction of three pan-European auctions called IDA is planned for all SIDC participants.

Within the same market area, many countries have maintained one or more local auctions, during which operators can only exchange energy with other operators belonging to the same area. The number of these auctions, the types of products they handle, and their timing vary from country to country (see Table 2.7).

Table 2.7: Daily Auctions Schedule

Country	Product	Number of Daily Auctions	Time
Austria	15 min	1	15:00
Belgium	15 min	1	15:00
France	30 min	1	17:00
Germany	15 min	1	15:00
Netherlands	15 min	1	15:00
England	30 min	2	17:30-08:00
Switzerland	60 min	2	16:30-11:15
Spain and Portugal	60 min	6	14:00-17:00-21:00-01:00-04:00-09:00

Until September 2021, the Italian intraday market was characterized by seven auctions without continuous trading [54]. However, after that date, with the entry into the SIDC, these auctions were replaced by three inter-regional auctions involving the market zones of Slovenia and Greece, as well as internal market zones. The fact that many countries have chosen to maintain or introduce auctions within the intraday market indicates that in certain cases, continuous trading alone may not be efficient. Specifically, auctions are essential for assigning a price to the available transit capacity, which is crucial for the proper valuation of exchanged energy.

2.12 The evolution

The development and improvement of the SIDC is a top priority for all NEMOs and TSOs that have joined the project. The main planned evolution's include:

- Introduction of pan-European auctions that allow for the economic valorization of inter-zonal capacity.

- Expansion of product offerings to include currently non-standard products, such as block products in addition to hourly, half-hourly, and quarter-hourly products.
- Implementation of the "flow-based" methodology for capacity calculation, using parameters such as power transfer distribution factors (PTDFs).
- Expansion of participation to include other European countries.

2.13 IDA

In accordance with Article 55 of the CACM for the valorization of inter-zonal capacity, ENTSO-E has proposed the introduction of European auctions, known as IDA (intraday auctions), which has been subsequently accepted by ACER. Three pan-European implicit intra-day auctions are planned to be launched in January 2023 for the exchange of hourly, half-hourly, and quarter-hourly products: the first auction will take place at 15:00 on day D-1, the second at 22:00 on day D-1, and the third will be held at 10:00 on day D [55].

However, beyond these decisions, there is still an ongoing discussion regarding the optimal number of auctions to be introduced. On one hand, a high number of auctions would allow for a quick response to events (a characteristic of a continuous trading market), but it would reduce market efficiency by frequently interrupting continuous trading and reducing market depth. On the other hand, a low number of auctions would ensure greater liquidity during certain periods of the day but would not address the issue of optimal utilization of transmission capacity [56]. This is because the capacity remaining available after the auction would be allocated entirely in the continuous market and therefore not fully utilized.

Chapter 3

Analyses of the biggest intraday European market

3.1 Analyses

In this chapter, we conduct an analysis of four prominent intraday markets in Europe: the Iberian, German, French, and Italian ID markets. We begin by describing the market structure, including the types of products traded, the number of auctions, their integration with continuous trading, and the gate opening and closing times for each session. Subsequently, various statistical analyses are presented to investigate the price trends of each market in relation to the day-ahead auction session, the volumes exchanged during different time frames, the number of orders, and the price variations based on the temporal distance between submission and delivery time. Additionally, other aspects of the intraday market are explored. It is important to note that the historical data used for these analyses have been sourced from different market operators in distinct market areas. As a result, separate analyses have been conducted for each market, considering the available data. By examining the market structures and conducting statistical analyses, we aim to gain insights into the dynamics of these intraday markets. This analysis provides valuable information about the relationship between the intraday market and the day-ahead auction session, the trading volumes at different time intervals, the behavior of market participants based on the submission-delivery time, and other significant aspects. By understanding these characteristics, we can better comprehend the functioning and perfor-

mance of the intraday markets in Europe. It should be emphasized that the analysis is based on historical data and the specific conditions prevailing during the analyzed period. Factors such as market regulations, renewable energy integration, and market participant behavior can influence the observed trends and patterns. Therefore, the findings and conclusions drawn from this analysis are applicable to the specific time period and should be interpreted in the context of the underlying market conditions.

3.2 Iberian market

The Iberian electricity market, known as the MIBEL area, encompasses Portugal, Spain, and Andorra [47]. Market coupling with the rest of Europe is managed by the designated market operator, OMIE. Historically, the intraday market in the MIBEL area consisted of multiple auction sessions until 2018 [57]. However, with the introduction of the Xbid platform, the market structure was reconfigured into six auctions plus continuous trading. These auctions manage the price areas of Portugal and Spain, as well as the capacity interconnections of Spain-Portugal, Spain-Morocco, and Spain-Andorra. Furthermore, they facilitate continuous cross-border trading with other European countries that are part of the SIDC. The auctions provide the opportunity to trade energy up to four hours before the real-time delivery, offering different programming horizons for each session [20]. The specific programming horizons for each auction session are outlined in Table 3.1.

Table 3.1: Iberian market auctions

	1	2	3	4	5	6
Gate opening	14.00 D-1	17.00 D-1	21.00 D-1	1.00 D	4.00 D	9.00 D
Gate closing	15.00 D-1	17.50 D-1	21.50 D-1	1.50 D	4.50 D	9.50 D
Time horizon	1-24 D	21-24 D-1 ; 1-24 D	1-24 D	5-24 D	8-24 D	13-24 D

Continuous trading commences immediately after the conclusion of the initial auction and facilitates the exchange of energy between market participants within the same zone or across different zones, subject to available interconnection capacity. Participants have the opportunity to engage in trading activities up to one hour prior to the delivery time, with transactions occurring in thirty rounds as depicted in Figure 3.1.

ROUNDS "D" AND "D+1"																								SESSION												
DAY	OPENING	CLOSING	ROUND																																	
D-1	14:00	15:00	17	17	18	19	20	21	22	23	24														M1 14:00-15:00 [1-24]											
D-1	15:00	15:10	18	18	19	20	21	22	23	24																										
D-1	15:30	16:00	18	18	19	20	21	22	23	24	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24		
D-1	16:00	17:00	19	19	20	21	22	23	24	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24			
D-1	17:00	17:50	20	20	21	22	23	24	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24				
D-1	17:50	18:00	20	20																								M2 17:50-18:00 [25-24, 1-24]								
D-1	18:00	19:00	21	21	22	23	24	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24					
D-1	19:00	20:00	22	22	23	24	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24						
D-1	20:00	21:00	23	23	24	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24							
D-1	21:00	21:50	24	24	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24								
D-1	21:50	22:00	24	24																								M3 21:50-22:00 [1-24]								
D-1	22:00	23:00	1	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24									
D-1	23:00	0:00	2	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24										
D	0:00	1:00	3	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24											
D	1:00	1:50	4	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24												
D	1:50	2:00	4	4																								M4 1:50-2:00 [1-24]								
D	2:00	3:00	5	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24													
D	3:00	4:00	6	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24														
D	4:00	4:50	7	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24															
D	4:50	5:00	7	7																								M5 4:50-5:00 [1-24]								
D	5:00	6:00	8	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24																
D	6:00	7:00	9	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24																	
D	7:00	8:00	10	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24																		
D	8:00	9:00	11	11	12	13	14	15	16	17	18	19	20	21	22	23	24																			
D	9:00	9:50	12	12	13	14	15	16	17	18	19	20	21	22	23	24																				
D	9:50	10:00	12	12																								M6 9:50-10:00 [11-24]								
D	10:00	11:00	13	13	14	15	16	17	18	19	20	21	22	23	24																					
D	11:00	12:00	14	14	15	16	17	18	19	20	21	22	23	24																						
D	12:00	13:00	15	15	16	17	18	19	20	21	22	23	24																							
D	13:00	14:00	16	16	17	18	19	20	21	22	23	24																								

Figure 3.1: Trading time-line for the Iberian intraday market

Market participants in the Iberian intraday market have the flexibility to engage in continuous trading even during auction sessions. However, they are not allowed to exchange energy for the same time horizon covered by the auctions. For instance, during session number 3 starting at 9 p.m. (D-1) and covering energy for all 24 hours of day D, participants can only trade energy in continuous trading for the hours between 11 p.m. and 12 p.m. on day D. The Iberian intraday market can be characterized as a hybrid trading model, wherein market agents can choose between auctions or continuous trading based on their specific requirements and preferences. An analysis conducted by [55] revealed that four out of six zones with the highest energy trading volumes in the intraday market implemented IDAs (Intraday Auctions). This is attributed to the increased market efficiency during auctions. The study also emphasizes that liquidity and the efficient utilization of cross-zonal capacity are enhanced during auctions compared to continuous trading. Bellenbaum et al. (2014) [58] explain that high liquidity is closely related to a large number of market participants, while Lanfranconi et al. (2019) [59] argue that auctions ensure an efficient allocation of cross-zonal capacity in the intraday market compared to continuous trading. In general, continuous trading in the Iberian market follows the "first-come, first-served" rule, prioritizing speed of bids rather than their quality. Auctions, on the other hand, involve the aggregation of offers and the coupling of the market agent with the lowest ask price and the one with the highest bid price. Implicit intraday auctions in the

Iberian market contribute to its reputation as one of the most liquid intraday markets in the European Union [60].

3.3 Sources

In this section, we present the statistical analyses conducted on the data of orders submitted and matched in the Iberian intraday markets. The focus of these analyses was on the prices and volumes of different types of orders submitted in continuous trading, as well as the outcomes of matching in continuous trading and auctions. Additionally, analyses were performed to examine the variation in volumes and prices based on the time interval between order submission and delivery. These analyses encompassed different periods of the year and various hours throughout the day. The data received from the Iberian market operator [60], OMIE, for the auctions included volumes and prices of exchanged energy. For continuous trading, the data only pertained to the submitted orders and did not include those that resulted in positive matches. The data for continuous trading, received in Microsoft Excel files, encompass the following variables:

- Date of order submission
- Contract indicating the energy delivery time
- Zone from which the order originates
- Agent who submitted the order
- Production unit
- Quantity
- Offer type (buy or sell)
- Execution restriction
- Validity restriction
- Reduced quantity (in the case of iceberg orders)

- Time of order submission

To expedite the statistical analyses, the software "R" was employed, enabling the segmentation of orders based on the months of the year, hours of the day, and temporal distance between order submission and delivery.

3.3.1 Volumes traded in the different sessions of the SIDC from 2018 to 2020

The first analysis conducted focuses on the volumes traded in each individual auction and in continuous trading from the entry into the SIDC on June 13, 2018, until December 31, 2020.

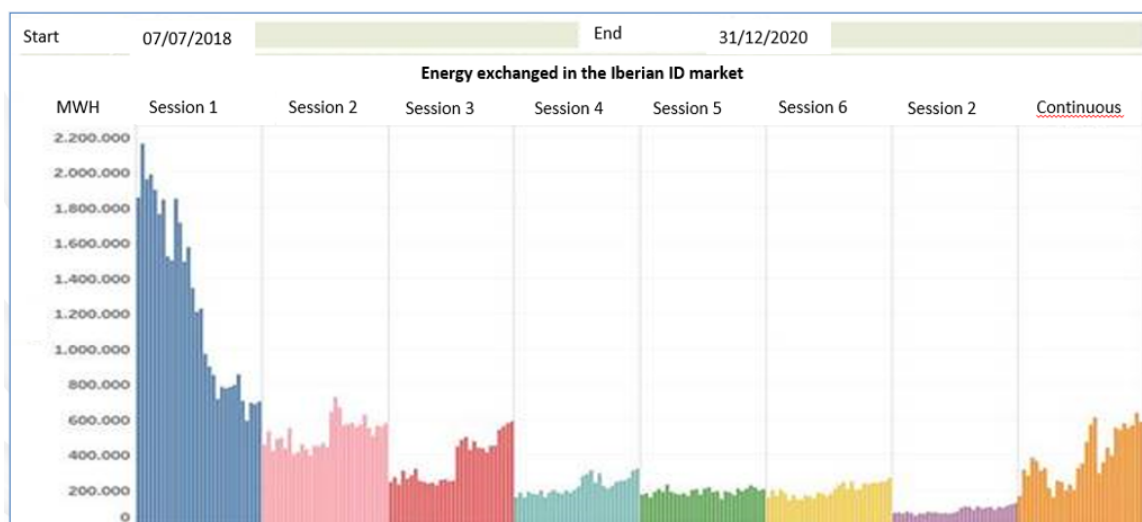


Figure 3.2: Volumes traded in the Iberian ID market (source: OMIE)

By observing Figure 3.2, it can be noticed that the majority of volumes are still traded during the first three auctions. However, as December 2020 approaches, the utilization of continuous trading is significantly increasing, indicating a growing need to negotiate energy closer to the actual delivery time in a market ready to exploit non-programmable renewable sources more extensively. There are two 'session 2' as this auction involves trading products for all 24 hours of day D (the first of the two session 2s) as well as products for the hours from 21:00 to 24:00 of day D-1.

3.3.2 Prices of auctions and prices of orders submitted in the continuous market

This analysis focuses on the prices resulting from auctions and the prices at which orders are submitted in the continuous market. The first graph in Figure 3.3 displays the density of auction prices for a selected month (January is provided below as an example, but the analysis was conducted for all other months as well, with similar results).

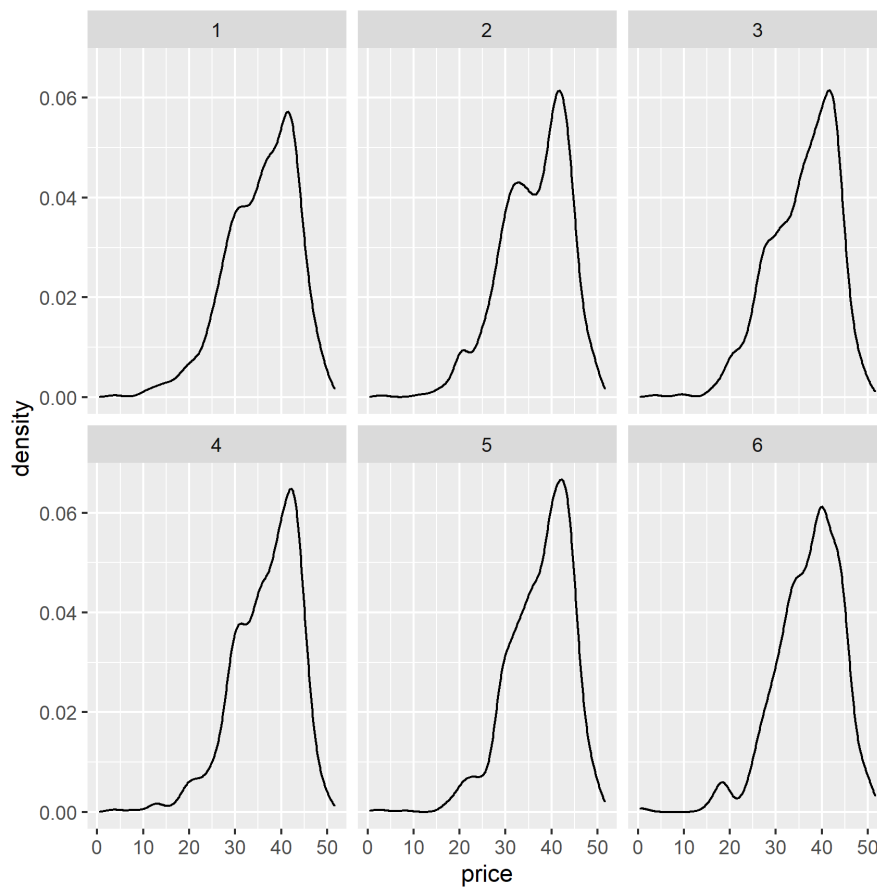


Figure 3.3: Density curves of prices [€/MWh] resulting from the six auctions in January 2020

Table 3.2 presents the average prices, standard deviations, and number of bids for all six auctions, as well as the continuous market, for each month in 2020.

Table 3.2: Average Prices, Standard Deviations, and Number of Bids for Auctions

Auction	January	February	March	April	May	June	July	August	September	October	November	December	Year
Auction 1													
Price	40.78	35.69	27.57	17.73	21.31	30.86	34.53	36.08	41.93	36.04	41.7	41.99	33.85
Standard Deviation	8.01	7.55	7.21	6.54	7.28	6.57	6.1	5.92	9.09	10.91	8.89	12.56	11.34
Number of Bids	1488	1392	1486	1440	1488	1440	1488	1488	1440	1490	1440	1488	17568
Auction 2													
Price	41.28	36.24	28.47	17.94	21.62	31.15	35.21	36.74	42.31	36.46	41.68	42.81	34.33
Standard Deviation	7.8	7.26	7.22	6.6	7.41	6.82	6.13	6.13	9	10.71	8.57	12.19	11.31
Number of Bids	1736	1624	1726	1680	1736	1680	1736	1736	1680	1738	1680	1736	20488
Auction 3													
Price	40.67	35.92	27.92	17.68	21.28	30.53	34.84	36.01	41.73	35.48	41.04	42.21	33.77
Standard Deviation	7.5	7.16	7.13	6.69	7.48	6.95	5.97	5.84	8.92	10.7	8.75	12.27	11.21
Number of Bids	1488	1392	1486	1440	1488	1440	1488	1488	1440	1442	1440	1488	17520
Auction 4													
Price	41.94	36.72	28.59	17.74	21.14	30.73	35.64	36.61	42.69	36.81	42.22	43.7	34.63
Standard Deviation	6.84	7.06	7.19	6.47	8.62	6.86	5.86	6.12	8.9	10.56	8.55	12.04	11.45
Number of Bids	1240	1160	1240	1160	1200	1200	1240	1240	1200	1240	1200	1240	14560
Auction 5													
Price	43.43	37.54	29.44	18.6	21.64	31.34	36.33	37.4	43.78	38.05	43.09	45.62	35.5
Standard Deviation	5.6	6.73	7.1	6.91	8.71	6.72	5.76	6.23	8.67	10.11	7.99	10.99	11.45
Number of Bids	1054	986	1054	1054	1054	1020	1054	1054	1020	1020	986	1054	12410
Auction 6													
Price	43.67	37.04	29.41	18.65	22.21	31.8	36.78	37.65	43.3	37.18	43.77	45.99	35.54
Standard Deviation	6.34	7	6.82	6.85	7.21	6.77	5.58	6.13	8.31	10.08	7.88	9.83	11.19
Number of Bids	720	696	744	720	696	720	744	672	672	744	696	696	8520
Continuous sell													
Price	54.16	47.98	42.37	30.2	32.79	37.97	43.44	44.52	49.06	44.82	51.18	52.42	44.21
Standard Deviation	13.15	14.87	20.66	16.21	17.32	10.81	12.69	14.89	15.95	17.16	17.45	18.79	17.69
Number of Bids	335759	272366	327377	326326	310372	280509	296122	296790	266475	287203	328545	297654	3625498
Continuous buy													
Price	28.49	25.59	22.13	12.16	16.53	24.12	27.93	30.04	36.3	29.06	34.16	36.73	27.39
Standard Deviation	14.38	12.94	9.76	8.23	9.34	11.02	11.88	11.9	13.11	14.34	15.12	15.24	14.44
Number of Bids	364899	295395	281163	263255	267468	284911	309798	306353	283759	292563	356516	335610	3641960

Figure 3.4 shows the monthly trend of average prices while Figure 3.5 illustrates the number of bids for the auctions.

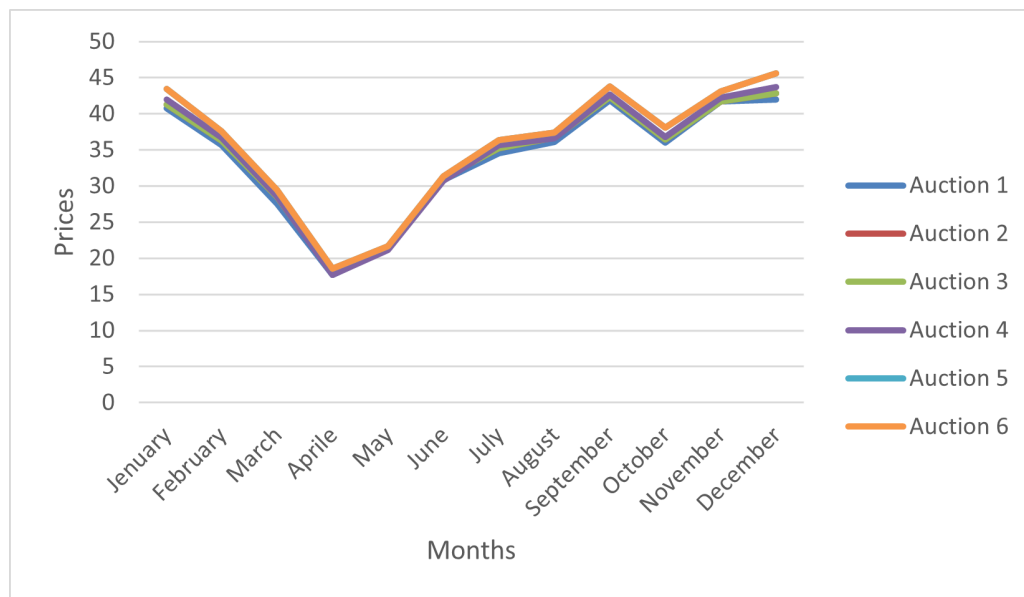


Figure 3.4: Monthly price trend for the six auctions in the Iberian market

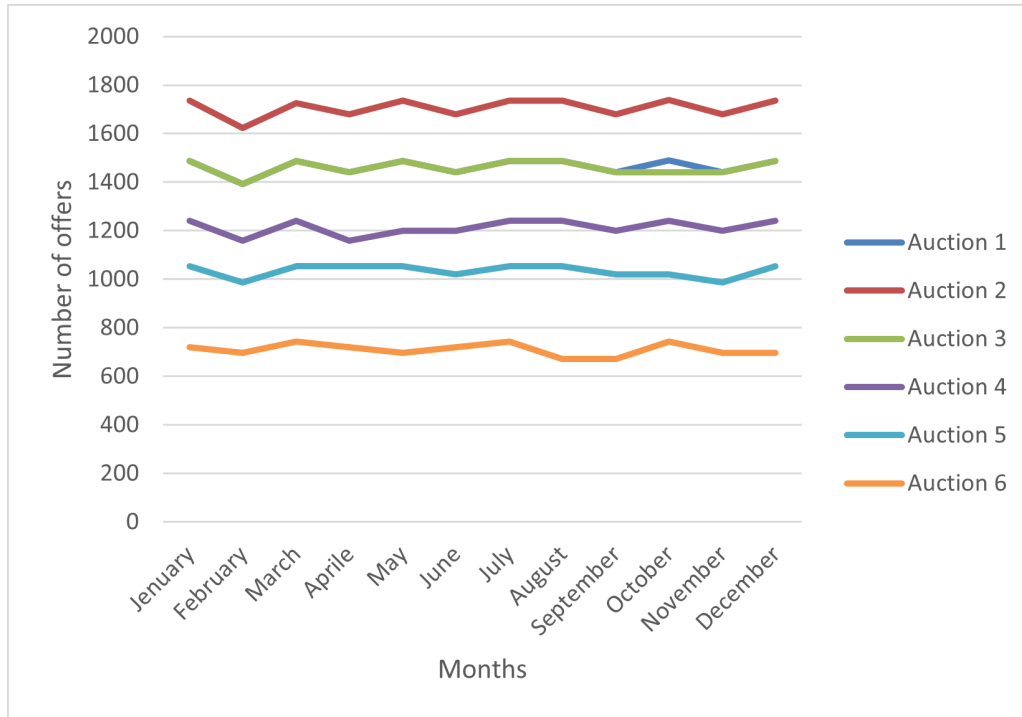


Figure 3.5: Monthly number of orders submitted for the six auctions in the Iberian market

The final graph pertaining to this second analysis is represented in Figure 3.6, showcasing the temporal evolution of the first and third quartiles of the prices associated with buy and sell offers presented during continuous trading.

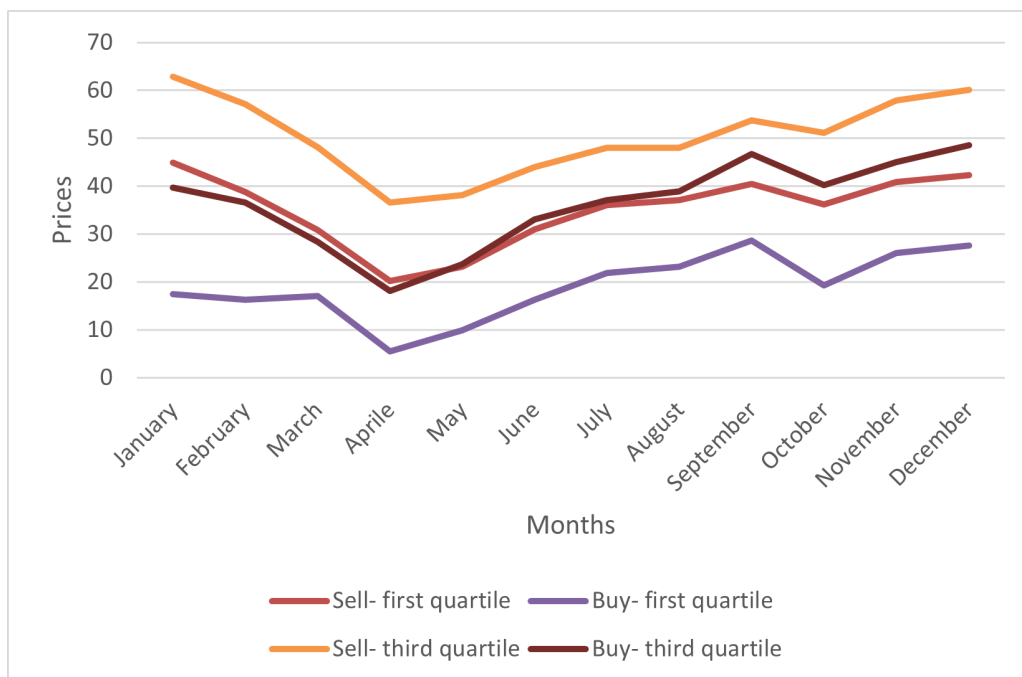


Figure 3.6: First and third quartile of price of orders (€/MWh) presented in continuous trading divided into buy and sell

In Figure 3.4, it can be observed that auction prices exhibit similar trends, while the majority of offers are submitted during the first two auctions and decrease in number as the sixth auction is reached. Prices, on the other hand, are significantly higher during the winter months (40-45 €/MWh) compared to the summer months (20-30 €/MWh). In continuous trading, there are a greater number of offers with higher average prices for sale and lower average prices for purchase, indicating a low match rate in this market session. An interesting parameter is the relatively low standard deviation (7 €/MWh) for the auctions, indicating that the majority of accepted offers are centered around the mean, while it is higher in continuous trading. The graph in Figure 3.6 illustrates how many offers in continuous trading are submitted with the aim of achieving a high profit without a real possibility of matching. In fact, the third quartiles for sale and purchase are widely separated, while the second quartiles show slight overlap.

3.3.3 Temporal distance in hours between the order placement and delivery

The third analysis focuses on orders in continuous trading. Specifically, the aim is to demonstrate the temporal proximity to the delivery at which market operators tend to place buy and sell orders based on various execution constraints. This analysis aims to examine the timing patterns of order submissions with respect to delivery deadlines, shedding light on the strategies employed by market participants to optimize their trading activities within the given execution restrictions.

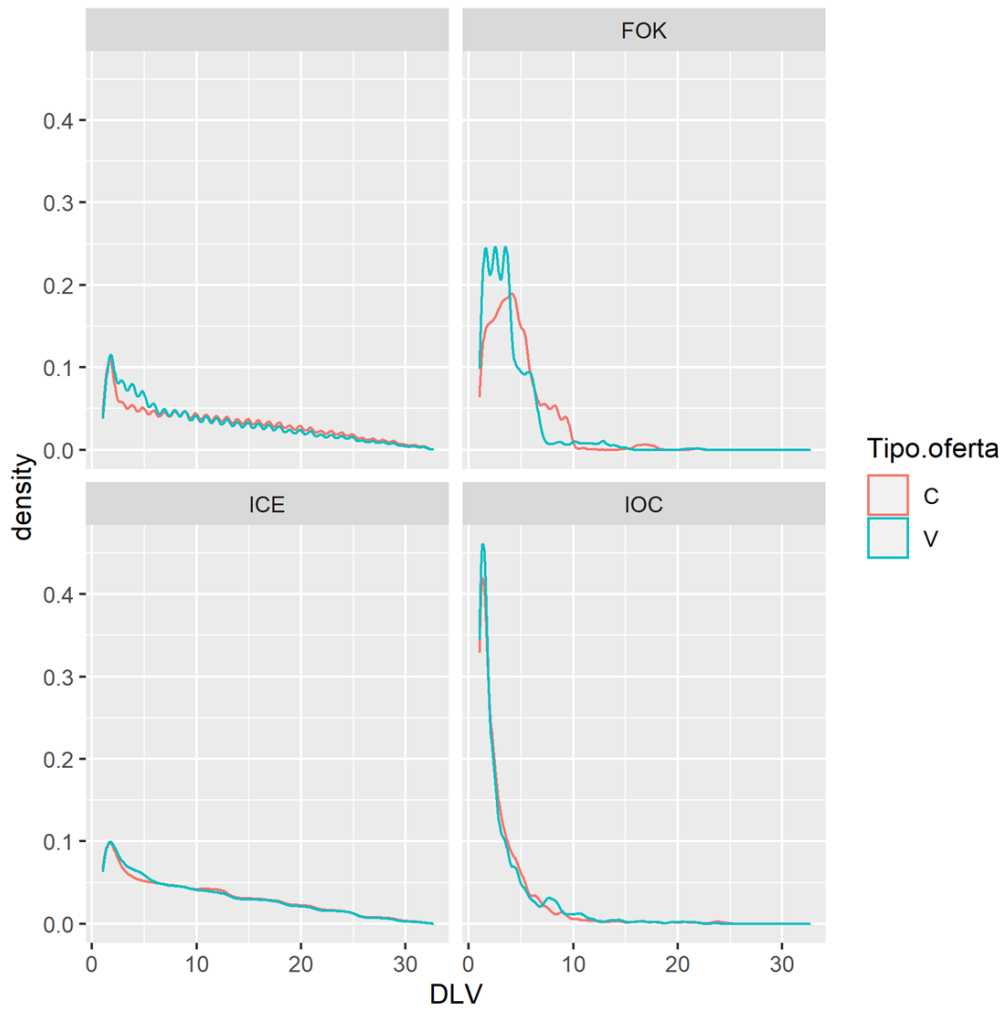


Figure 3.7: Density of the number of orders submitted based on the time distance from delivery

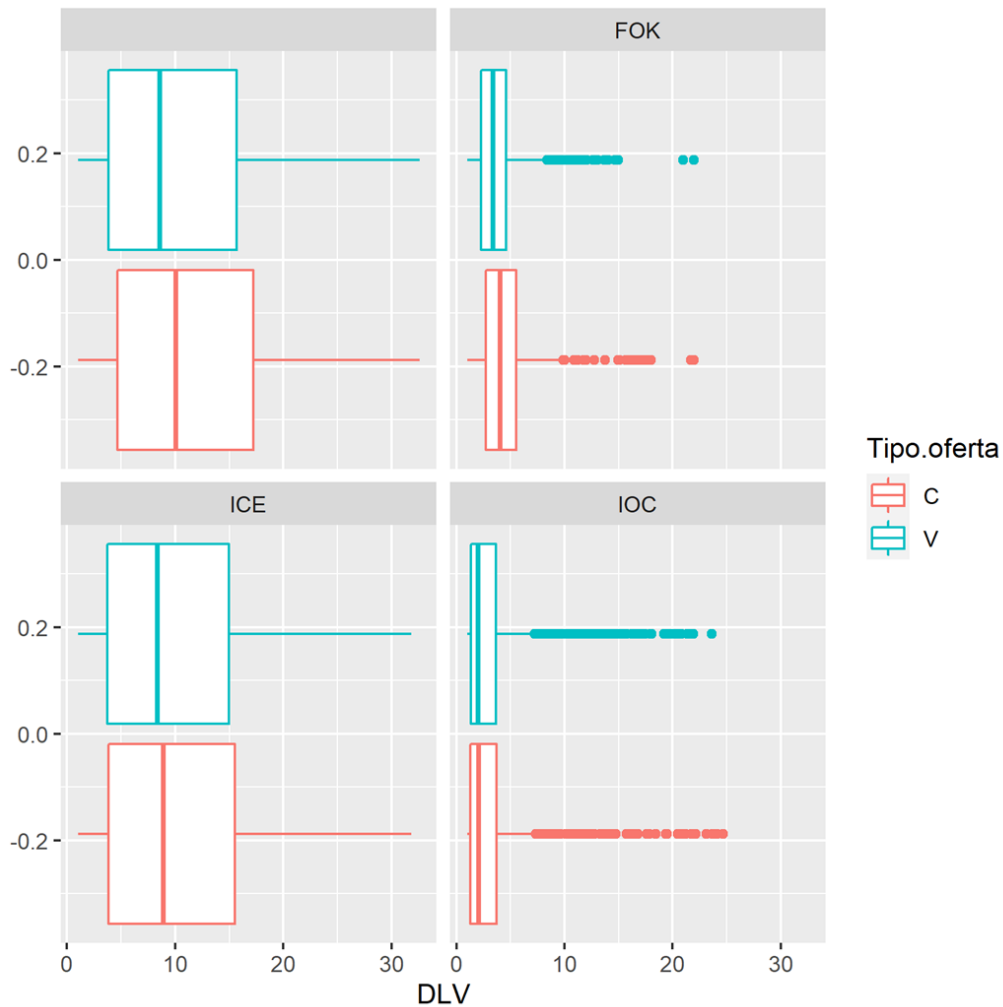


Figure 3.8: Quartiles of the number of orders submitted based on the time distance from delivery

Based on these analyses, it is evident that for IOC and FOK conditions, 50% of the orders occur between 2 and 4 hours before the delivery deadline. However, a significant portion of orders deviates considerably from the mean towards the right, indicating either a strategic approach or a lack of market prediction ability. IOC orders exhibit a distinct peak of orders placed very close to the delivery time (around 2.5 hours) that gradually decrease thereafter. On the other hand, FOK orders show a peak within the 2 to 4-hour timeframe before delivery, followed by a sharp decline after the 5th hour. For NON and ICE conditions, 50% of the orders occur between 5 and 15 hours before delivery, but they do not exhibit any significant outliers (i.e., values deviating significantly from the mean). These types of orders, remaining in the order book, do not necessarily require immediate execution. In contrast, for IOC and FOK orders, there is a tendency to submit offers close to the delivery time (2-3 hours), while for ICE

and NON orders, as depicted in Figure 3.7, a considerable number of orders are presented at greater time intervals.

3.3.4 Number, prices, volumes, and temporal distance between the order placement and delivery, based on execution restrictions.

For the fourth analysis, Table 3.3 presents the sell orders, while Table 3.4 displays the buy orders, summarizing the number of offers, average prices (€/MWh), average volumes (MWh), and average temporal distance (hours) between placement and delivery for each execution restriction. Examining these results, it is evident that prices decrease during the summer months and are consistently higher for sell orders compared to buy orders across all types of orders and restrictions. The most frequent orders are NON, while FOK and IOC orders are less prevalent in comparison to others. IOC and FOK orders also exhibit the closest proximity to delivery. On the other hand, ICE orders have the highest volumes.

Table 3.3: Summary of Sales Orders

	Sales				
	January	May	August	November	Year
NONE					
Number of orders	309516	285909	269461	299892	3331007
Average quantity	12.82	10.39	11.11	10.84	11.4
Average price	54.71	33.31	44.91	51.78	44.67
Distance	10.53	10.41	10.79	10.05	10.35
ICE					
Number of orders	25886	24333	26157	28508	307431
Average quantity	74.98	69.42	66.75	68.44	67.41
Average price	47.81	26.75	40.96	44.96	39.3
Distance	9.6	9.81	10.38	9.89	9.97
FOK					
Number of orders	3	8	865	29	1621
Average quantity	28.37	80.54	83.87	71.38	79.02
Average price	35.33	23.12	31.47	49.6	31.75
Distance	3.26	13.51	4.39	5.47	3.74
IOC					
Number of orders	354	122	307	116	2189
Average quantity	76	56.63	92.34	91.75	88.8
Average price	45.54	22.22	37.17	37.51	35.51
Distance	3.7	2.93	4.12	3.15	3.21

Table 3.4: Summary of Purchase Orders

	Purchases				
	January	May	August	November	Year
NONE					
Number of orders	337878	244002	260781	327571	3339333
Average quantity	19.86	10.11	14.31	11.83	13.45
Average price	27.82	16.38	29.79	33.78	27.12
Distance	11.21	11.78	11.79	12.38	11.56
ICE					
Number of orders	26790	23264	25448	28497	304999
Average quantity	79.49	74.22	74.53	64.66	69.36
Average price	36.78	18.13	32.73	38.32	30.68
Distance	9.85	9.66	10.45	10.77	10.29
FOK					
Number of orders	3	32	9	268	8811
Average quantity	35.43	35.53	65	64.57	77.92
Average price	20.63	26.19	36.92	47.63	14.49
Distance	6.49	8.72	1.33	3.12	4.51
IOC					
Number of orders	228	170	115	180	1813
Average quantity	94.35	82.97	92.28	108.49	76.91
Average price	40.96	17.46	50.3	59.89	47.31
Distance	4.57	2.68	2.63	2.62	2.57

3.3.5 Prices of orders presented during the 24 hours of the day

In this analysis, the box plot is presented for the average prices of the 24 hours of January and April 2020, both for auction prices and continuous market offers. The box plots display the 50% of prices around the mean, effectively excluding any potential outliers that could distort the overall average (given the significantly high standard deviation observed in the prices presented in the continuous market).

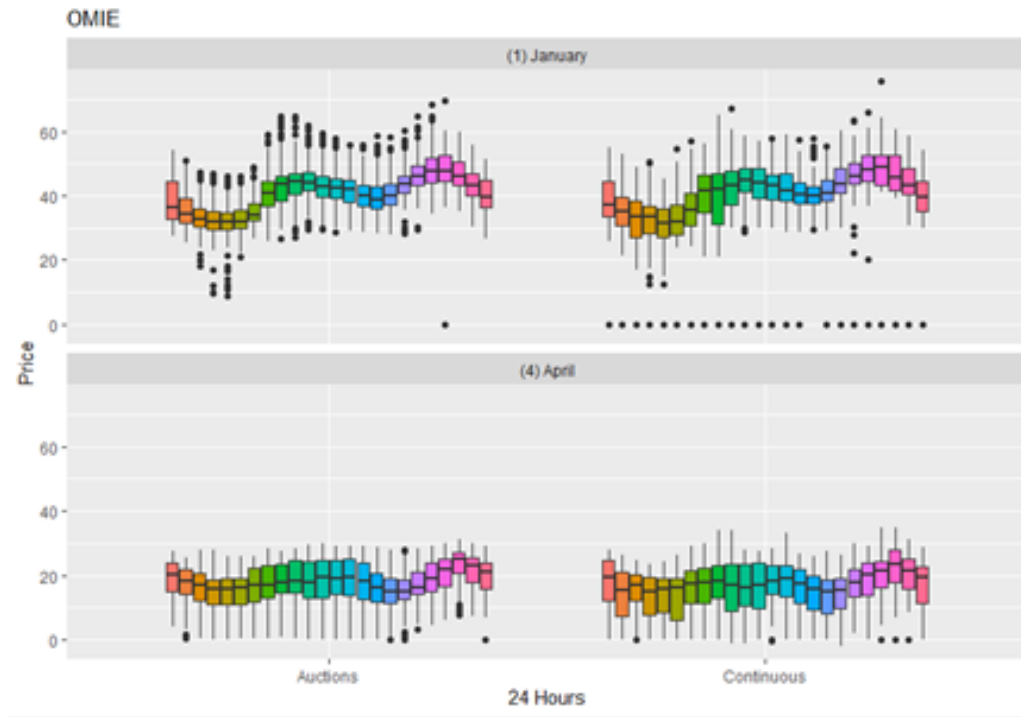


Figure 3.9: quartiles of prices (€/MWh) for auctions and continuous market trading during the 24 hours of January and April 2020

It is noteworthy that the price trends in continuous market trading are highly similar to those observed in auctions. This indicates that auctions can provide clear price signals for market operators engaging in continuous trading activities.

3.3.6 Conclusions on the Iberian intraday market

In this market, the majority of volumes are traded during auctions, although there has been a significant increase in continuous trading offers in recent years. One possible reason for this trend is the growing presence of renewable energy sources in the market. Across all six auctions, the marginal price hovers around €30-40/MWh, which serves as a favorable price signal for participants to submit continuous offers with a high likelihood of matching. However, a considerable number of offers in continuous trading have selling (buying) prices that are too high (low) compared to the prices established in auctions. This suggests that market operators, following a first-come-first-served rule, aim to maximize their profits by securing extremely favorable matches. Given the frequent occurrence of auctions, there is no need to sell/buy energy at less favorable prices unless they are very close to the delivery time. The majority

of offers are submitted between 2 and 4 hours before the delivery, following the price signals from the auctions. Thus, continuous trading is gaining importance, particularly due to the need for trading activities to be conducted closer to the delivery hour. However, the presence of a sufficient number of auctions ensures that operators can trade the majority of volumes with high liquidity, allowing them to adopt various strategies to increase their profits between auctions. When approaching the delivery hour, the absence of auctions compels operators to submit orders at more competitive prices in order to increase the likelihood of finding a match more quickly. This maintains the efficiency and liquidity of the market even during continuous trading. These results has been published in [23]

3.4 German market

The German electricity market is operated by EPEX Spot, which oversees energy exchanges in several North-Central European countries [61]. Unlike the Iberian market, participants in the German market have the flexibility to trade not only hourly products but also half-hourly and quarter-hourly products. The German Intraday (ID) market, in particular, commences at 3:00 p.m. after the closure of the day-ahead market. It consists of a single auction conducted for quarter-hourly products and continuous trading for hourly, half-hourly, and quarter-hourly products. Market participants have the option to utilize the SIDC (Single Intraday Coupling) platform to trade with other zones affiliated with SIDC until one hour before the delivery time. Alternatively, they can submit orders within the internal German ID market, allowing trading until five minutes before the delivery time. However, when utilizing the internal German ID market, participants can only trade with agents from the same zone. The execution restrictions applied to orders in the German ID market are similar to those in the Iberian market. Table II provides a summary of the German ID market, highlighting its key characteristics and features.

Table 3.5: German ID market parameters

Market	Opening	Closing	Time horizon	Products available
Auction	D-45	15:00 (d-1)	1-24 d	QH
Continuous 1	15:00 (d-1)	D-5'	15:05-24 d-1; 1-24 d	H
Continuous 2	15:30 (d-1)	D-5'	15:35-24 d-1; 1-24 d	HH
Continuous 3	16:00 (d-1)	D-5'	16:05-24 d-1; 1-24 d	QH

3.5 Sources

The German market operator, EPEX, has provided data for all days of 2020, including:

- Prices for each hour derived from the day-ahead market auction held at 12:00 PM the day before.
- Prices for each quarter-hour derived from the German intraday market auction held at 15:00 (this auction only includes quarter-hour products and is limited to the German area).

- Data on all orders submitted in the continuous intraday market, both through the SIDC platform for exchange with other European countries and through the ID platform for exchange within Germany only. The main difference between the platforms is that in SIDC, trading is possible until one hour before delivery, while in the ID platform, it is possible until five minutes before delivery.
- Final matching prices for each hour, half-hour, and quarter-hour in the continuous market. These prices differ from the proposed matching prices in the offers submitted by operators. For example, if a selling offer at €30/MWh is matched with a buying offer at €40/MWh, the final matching price is €40/MWh.

Due to the large volume of data (over one billion orders), which cannot be analyzed using Microsoft Excel, an application was developed to expedite the processing of information for four days of each month. Specifically, the 5th, 10th, 20th, and 25th days of each month were selected. Only orders with positive partial or total matches were included, and 30-minute products, which are fewer in number compared to hourly and 15-minute products, were excluded. These selections facilitated the analyses presented in the next chapter.

The following are the characteristics of orders in continuous trading:

- Order ID: unique identifier for the order.
- Initial ID: remaining original identifier after any modifications made by the operator to change characteristics such as volume or price (corresponds to the order ID).
- Parent ID: new identifier adopted after any modifications (different from the order ID).
- Entry time: time at which an order is submitted.
- Action code: indicates if the order was submitted, matched, partially matched, iceberg, modified, or canceled by the system or operator.
- Transaction time: indicates the time at which the action indicated by the action code occurred.
- Validity time: indicates the validity period of the order.

- Delivery start: indicates the start time of the delivery.
- Delivery end: indicates the end time of the delivery.
- Product: indicates the type of product (hourly, half-hourly, quarter-hourly, SIDC or ID).
- Delivery area: origin area of the order.
- Market area: Germany.
- Side: buy or sell.
- Price: price (€/MWh).
- Currency: €.
- Quantity: volume (MW).
- RevisionNo: indicates if the order has been modified and how many times.
- isUserDefinedBlock: indicates if the order is a block order.
- Execution restriction: indicates the execution restriction.

In this case as well, an R code was developed to divide the orders by months, hours of the day, and the time interval between order submission and delivery.

3.5.1 The percentages of matched orders, orders canceled by the operator, and orders canceled by the system after submission

The initial analysis focused on a single day selected from each season (January, April, August, and October). The percentages of orders that were submitted (A) and subsequently matched (M), canceled by the operator (D), or canceled by the system (X) were examined. This analysis provides insights into the order dynamics, including the rate of successful matches and the frequency of cancellations by both the operator and the system.

Table 3.6: Percentages of Matched (M), Operator Canceled (D), and System Canceled (X) Orders

Day	% M	% D	% X
15/01/2020	9.9	84.8	5.3
15/04/2020	9.3	85.6	5.0
15/08/2020	7.0	88.2	4.7
15/10/2020	5.6	91.8	2.6

It is observed that the majority of orders submitted are subsequently canceled by the operator (85%), with only 5-10% being accepted. This indicates that operators employ specific strategies involving iterative order submission and immediate cancellation until a match is found. The high frequency of order submission and cancellation suggests the involvement of algorithmic trading executed automatically by computer systems.

3.5.2 Mean Prices for Submitted and Accepted Offers

The second analysis was conducted on the same days as the previous analysis. The average prices for offers submitted and accepted, as well as the average prices for successful matches, are presented.

Table 3.7: Sales (prices in €/MWh)

Day	Average Offer Price	Average Match Price
15/01/2020	94.39	35.69
15/04/2020	102.64	25.78
15/08/2020	67.47	29.92
15/10/2020	117.17	46.80

Table 3.8: Purchases (prices in €/MWh)

Day	Average Offer Price	Average Match Price
15/01/2020	9.65	40.15
15/04/2020	1.54	32.39
15/08/2020	11.54	32.99
15/10/2020	23.55	49.64

It can be observed that on average, the incoming prices are very high for sellers and very low for buyers. The average incoming prices for successful matches, however, are quite similar for both sellers and buyers, with slightly higher prices for buyers. This indicates that many

operators attempt to submit offers to buy and sell at highly favorable prices (i.e., significantly deviating from the resulting market-clearing price for the same hour), but the matches tend to converge around the prices of the day ahead market.

3.5.3 Comparison between continuous match incoming prices and auction prices

The third analysis was conducted on the selected 48 days of the year. For each market (XBID and ID) and for each product (H-hourly and QH-quarter-hourly), the incoming match prices for sell and buy orders were compared with the prices resulting from the auctions for the same days (the results for only one month per season are reported in the figures 3.10 and 3.11).

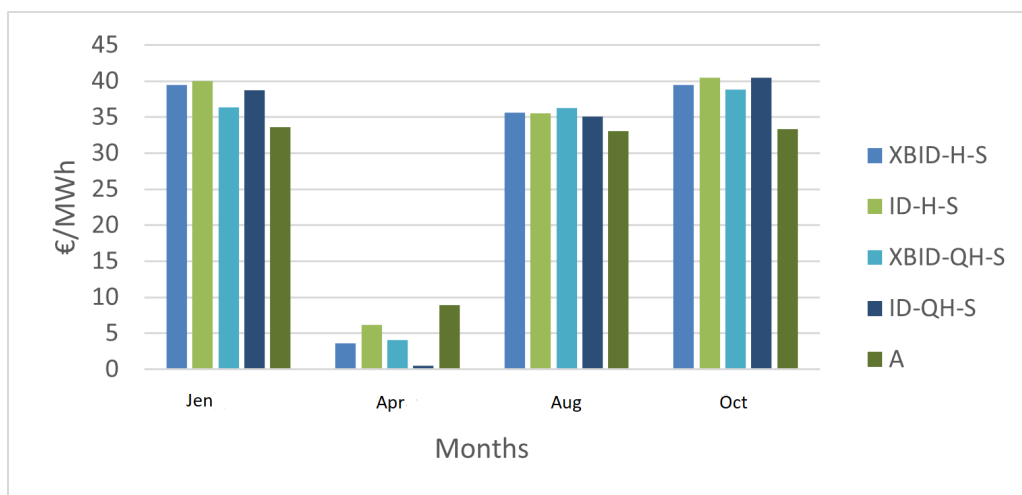


Figure 3.10: Average monthly selling prices [€/MWh] classified by product type traded on SIDC, ID, and auctions

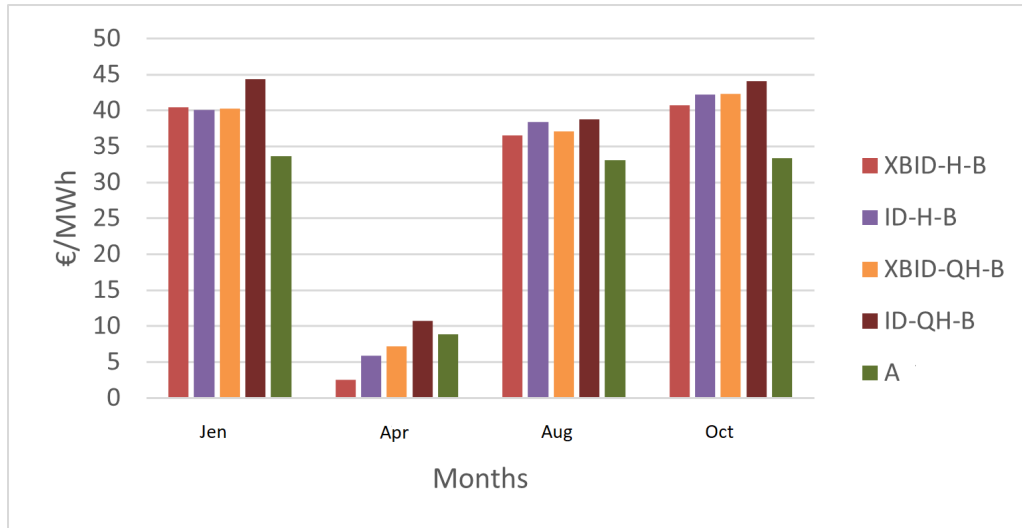


Figure 3.11: Average monthly buying prices [€/MWh] classified by product type traded on SIDC, ID, and auctions

This analysis does not reveal significant differences among the various types of markets in continuous trading. However, it is worth noting that auction prices are slightly lower, except for selling prices in the month of April, which are generally characterized by structurally low prices.

3.5.4 Time interval between order submission and delivery

The fourth analysis is conducted on the selected 48 days of the year, focusing on each market (SIDC and ID) and product type (hourly and quarter-hourly). It examines the average duration, in minutes, between the submission of an order (both sell and buy) and its delivery. This analysis aims to quantify the time gap between order placement and the actual delivery of traded products. By calculating the average duration, we can gain insights into the efficiency and timeliness of order execution in different markets and for different product types.

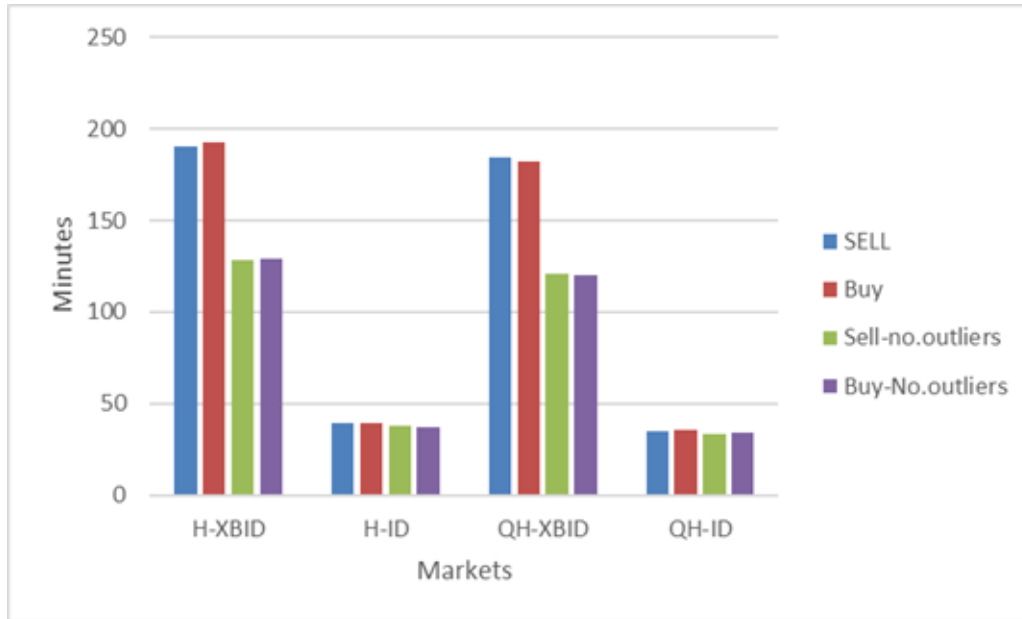


Figure 3.12: Average time (in minutes) elapsed between order submission and delivery, considering both all values and values within the first and third quartiles of the collected data (no outliers).

The observed results indicate that in the SIDC market, the average time interval between order submission and delivery revolves around 3 hours, while in the ID market, it revolves around half an hour. This discrepancy can be attributed to the different trading practices and regulations governing these markets. In the ID market, the primary focus is on trading energy within the 60 minutes preceding the delivery time. This allows market participants to make more immediate adjustments and react to real-time market conditions. Conversely, in the SIDC market, trading energy in the final 60 minutes before delivery is not permitted, leading to a longer average time interval between order submission and delivery.

3.5.5 Time interval between order delivery and match

The fifth analysis is conducted on the selected 48 days of the year, examining the average time interval in minutes between the last match of an order (both sell and buy) and its delivery, for each market (SIDC and ID) and each product type (H and QH).

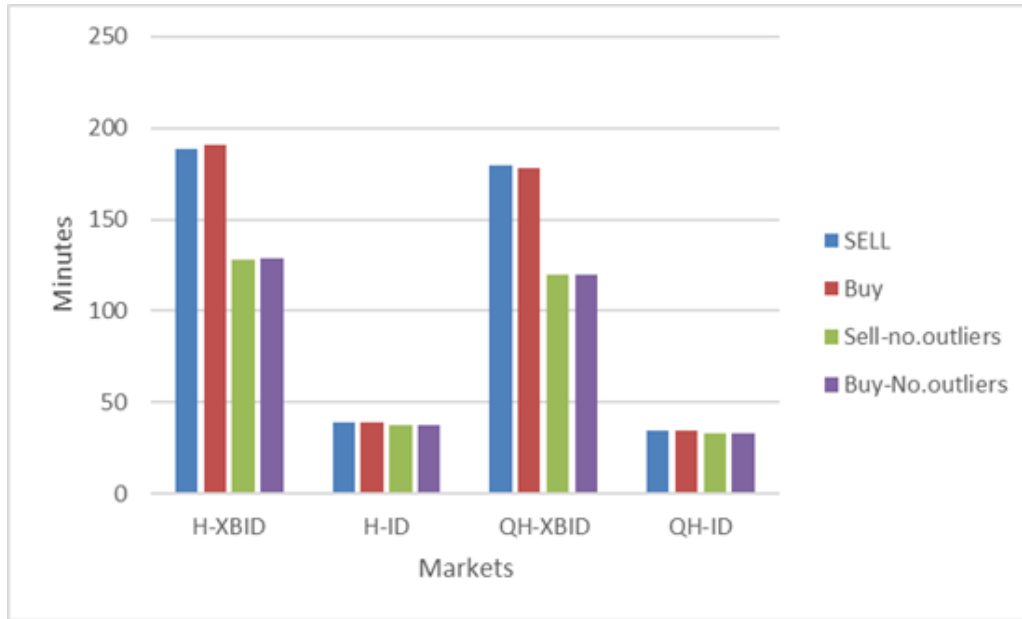


Figure 3.13: Average time (in minutes) elapsed between order delivery and match, considering both all values and values within the first and third quartiles of the collected data (no outliers).

It can be observed that the trend is very similar to the previous graph, indicating a reduced time interval between order submission and order matching.

3.5.6 Numbers and percentages of matched offers based on market and product

The sixth analysis is conducted on the selected 48 days of the year. Table 3.9 presents the number of offers and the percentage of matched orders in different markets (B=buy, S=sell).

Table 3.9: Number of submitted offers and percentages of matched offers

	XBID-H-S	XBID-H-B	XBID-QH-S	XBID-QH-B	ID-H-S	ID-H-B	ID-QH-S	ID-QH-B
Number of offers	741,484	725,010	949,778	971,713	323,416	331,445	762,423	784,522
Percentages (%)	13.26	12.97	16.99	17.38	5.78	5.92	13.63	14.03

It can be observed that generally there are more offers submitted in the SIDC market compared to the ID market, possibly because there are more opportunities for matches in a market that extends across Europe.

3.5.7 Entry prices of matched orders throughout the 24 hours of a day

The seventh analysis is performed over the 48 selected days of the year. Figures 3.14 and 3.15 show the trend of the entry prices for the hours of the day for different product types.

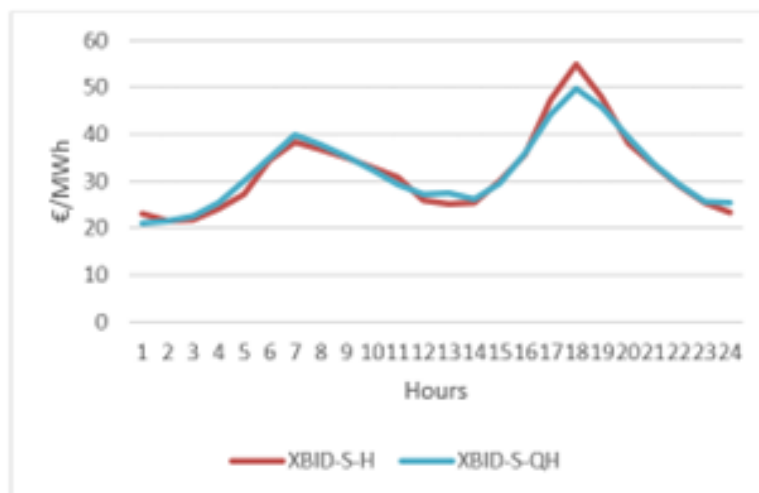


Figure 3.14: Variation of match selling prices in the SIDC market by hour

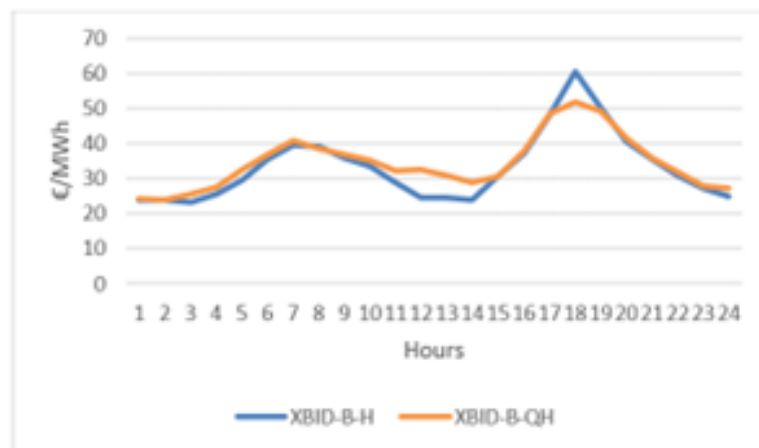


Figure 3.15: Variation of match buying prices in the SIDC market by hour

Only the graphs for the SIDC market are shown for brevity, as the prices in the ID market are very similar. It can be observed that there is a peak between 17:00 and 20:00, while prices decrease significantly in the early hours of the day, with a notable valley even during the midday hours.

3.5.8 Number of matched offers throughout the 24 hours of a day

The eighth analysis is conducted over the 48 selected days of the year and presents the number of matched offers throughout the 24 hours of the day.

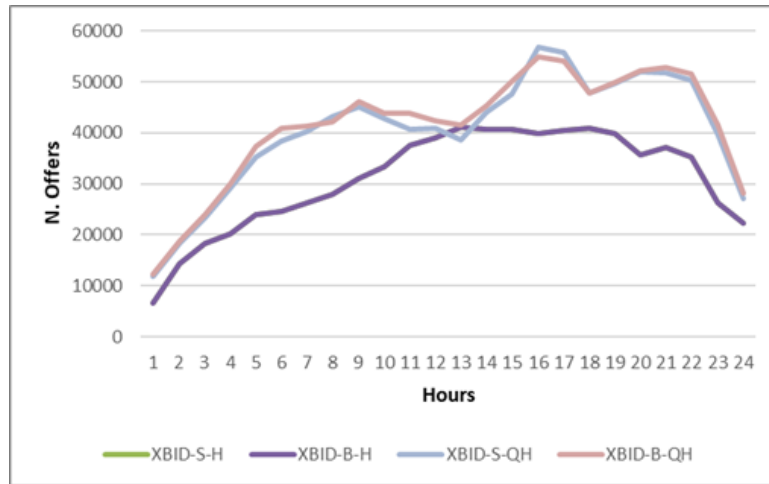


Figure 3.16: Number of offers matched during the 24 hours of the day in the SIDC market

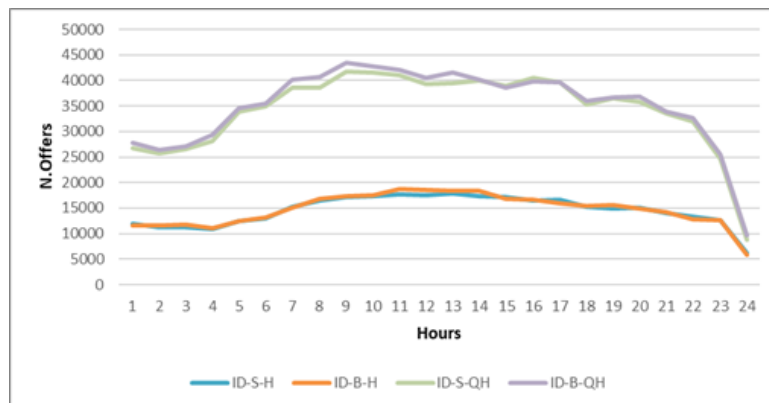


Figure 3.17: Number of offers matched during the 24 hours of the day in the ID market

It is observed that in SIDC, there is a peak in the number of offers when the incoming match prices are higher, while the number of offers decreases as the prices decrease. For the ID market, on the other hand, the number of offers shows a more linear trend. In both graphs, we confirm the higher number of offers for the quarter-hourly products.

3.5.9 Number of orders submitted varying with the hours before delivery

The 9th analysis is conducted over the 48 selected days of the year and presents the number of orders submitted at different time intervals relative to the delivery, using 16:00 as the reference delivery time.

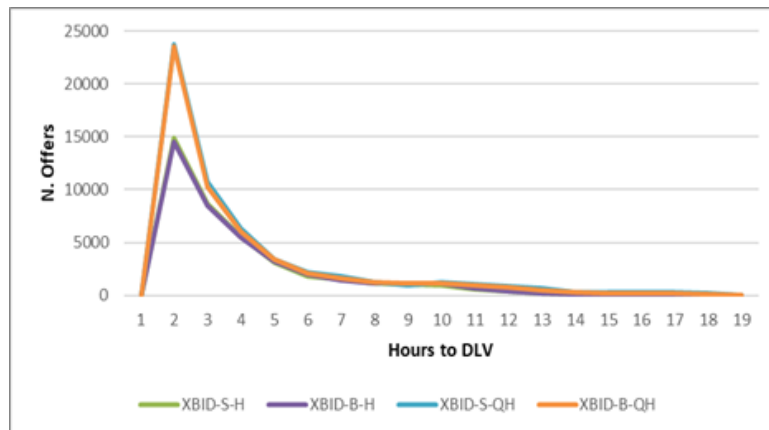


Figure 3.18: Number of offers submitted varying the distance between the submission and delivery time (for hour: 4 pm) in SIDC market

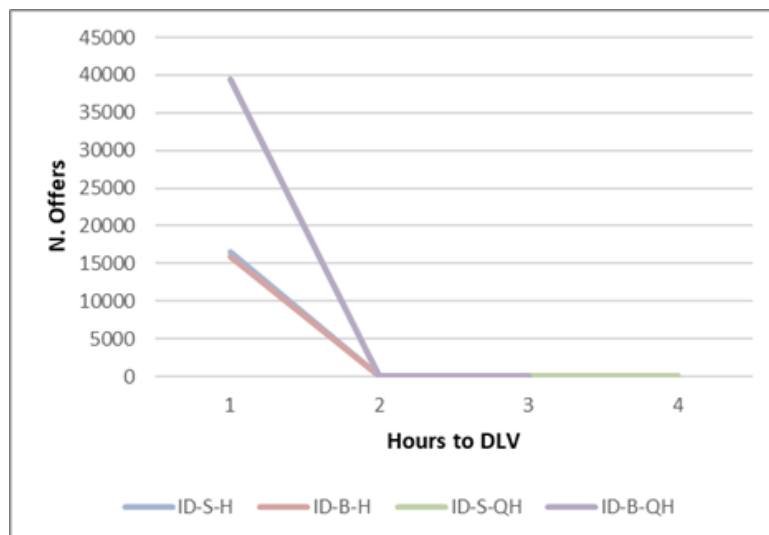


Figure 3.19: Number of offers submitted varying the distance between the submission and delivery time (for hour: 4 pm) in ID market

It is observed that the majority of orders in the SIDC market are submitted approximately three hours before the delivery, while in the ID market, most orders are submitted one hour before the delivery, with the reference delivery time being 16:00.

3.5.10 Incoming match prices varying with the hours before delivery.

The tenth analysis is conducted over the 48 selected days of the year and presents the prices of incoming match orders as they vary with the hours before the delivery time (16:00).

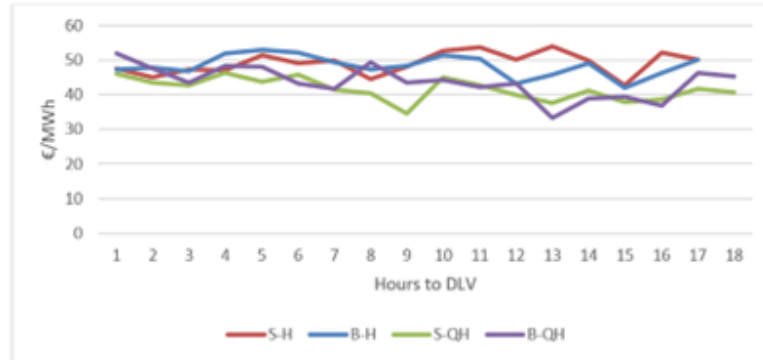


Figure 3.20: Match price of orders varying the distance between the submission and the delivery in SIDC market

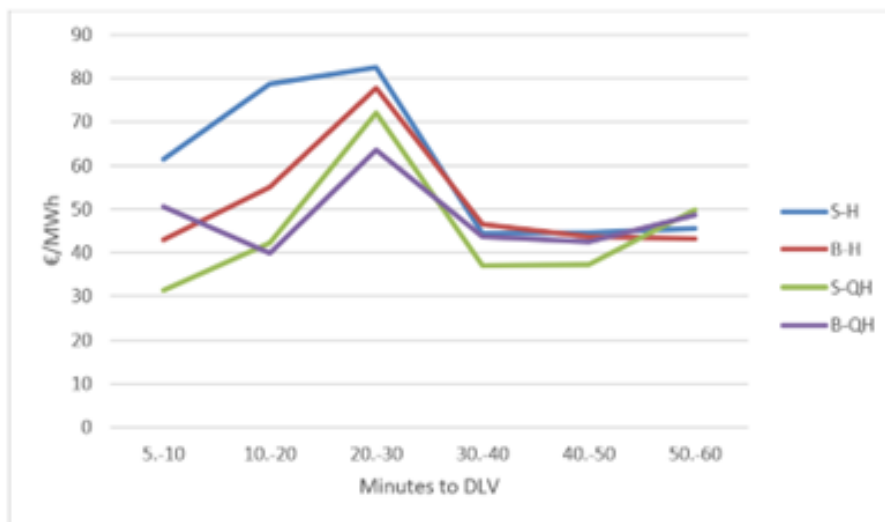


Figure 3.21: Match price of orders varying the distance between the submission and the delivery in ID market

It is observed that the price trend in the SIDC market remains relatively constant, with no significant differences observed among the different products. For the ID market, only the minutes of the last hour before delivery were analyzed, as the majority of offers are submitted during that time period, with a peak occurring approximately 30 minutes prior to delivery.

3.5.11 The quantity of orders accepted varies according to the product and execution condition

The eleventh analysis is conducted on the 48 days of the year and presents the percentage of accepted orders based on their type (AON, FOK, IOC, NONE-NOICE, IOCE, and NONE). In EPEX, ICE orders are classified as NONE orders, but here we have distinguished between NONE-NOICE orders and NONE orders (NON-NOICE + ICE). We observe that the most frequent orders overall are the NONE orders, which are orders without any specific restrictions. They are followed by IOC, ICE, FOK, and AON orders.

Table 3.10: Percentage of accepted orders by type

	AON	FOK	IOC	NONE-NOICE	ICE	NONE
XBID-H-S	0.0	3.6	13.1	75.5	7.8	83.3
XBID-H-B	0.0	2.8	12.5	75.7	8.9	84.7
XBID-QH-S	0.0	10.0	10.8	76.7	2.4	79.2
XBID-QH-B	0.0	11.1	11.1	75.6	2.2	77.8
ID-H-S	0.0	5.3	9.6	77.6	7.6	85.2
ID-H-B	0.0	5.3	10.0	77.3	7.4	84.7
ID-QH-S	0.0	11.1	9.5	76.6	2.9	79.5
ID-QH-B	0.0	10.6	10.4	75.7	3.3	79.0

Some observation can be done:

The majority of accepted orders in all markets and products fall under the "NONE" category, which represents orders without any specific restriction. This suggests that most participants prefer to submit orders without any additional conditions or limitations. The next most common order types are IOC (Immediate or Cancel) and FOK (Fill or Kill). These order types are designed to be executed immediately or not at all, ensuring either instant execution or complete cancellation. The percentage of accepted orders classified as "ICE" varies across different markets and products but generally remains relatively low. "ICE" orders may represent a specific type of order related to the ICE (Intercontinental Exchange) trading platform. AON (All or None) orders, which require the entire order to be executed in full or not at all, have a negligible presence in the data-set, with a 0% percentage across all market-product combinations. These observations provide insights into the distribution of different order types and their acceptance rates within the analyzed markets and products. It suggests that participants

commonly prefer flexible and unrestricted orders, with immediate execution or the option for cancellation if not immediately fulfilled.

3.5.12 Incoming match prices varying with the execution restrictions

The twelfth analysis is conducted over the 48 selected days of the year and reports the difference in incoming prices of accepted orders based on their restrictions.

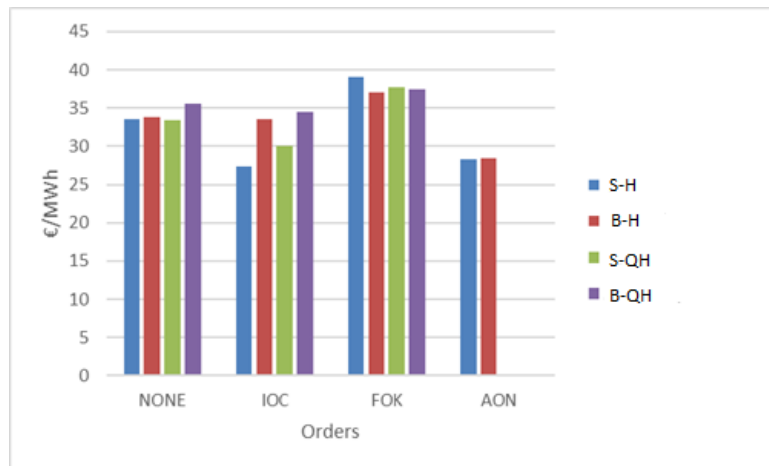


Figure 3.22: Incoming match prices according the execution restrictions for SIDC market

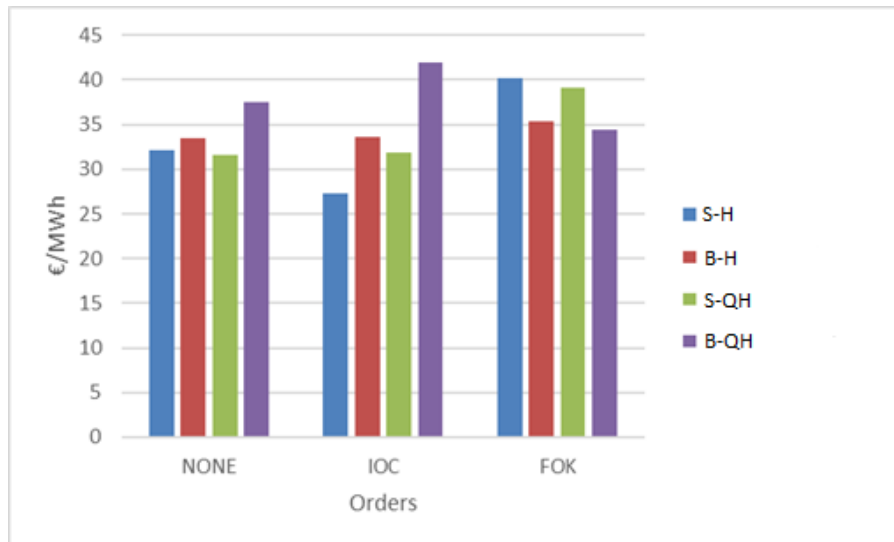


Figure 3.23: Incoming match prices according the execution restrictions for ID market

There are no significant differences in prices, except that FOK orders have slightly higher prices than the average, while IOC orders have slightly lower prices.

3.5.13 Comparison between DAM outgoing prices, ID auction prices, and ID continuous market matches

The fourteenth analysis is conducted on three different hours of a day for one month in each season. In our case, we considered the 15th of January, April, August, and November at 10 AM, 3 PM, and 8 PM. The average outgoing prices from the Day Ahead Market (DAM), ID auction, and ID continuous market (final match) are compared for the same hour of the same day. The same comparison is made for the hours from 10 AM to 11 PM of a single day. The Day Ahead Market and hourly ID continuous market prices have only one price for each hour, while the ID auction and quarterly ID continuous market have four prices for each hour. For simplicity, only one graph is presented as the trend for the different selected days is similar.

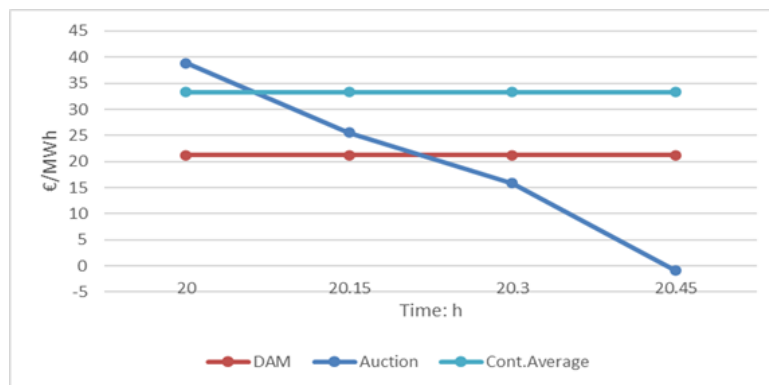


Figure 3.24: Comparison of DAM, ID auction, and ID continuous (hourly product) prices for 8 PM on April 15 - H products.

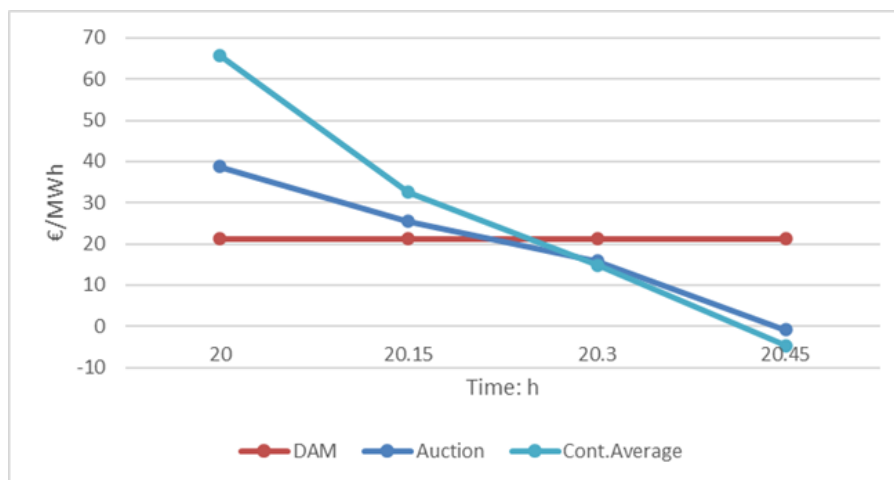


Figure 3.25: Comparison of DAM, ID auction, and ID continuous (quarter-hourly product) prices for 8 PM on April 15 - QH products.

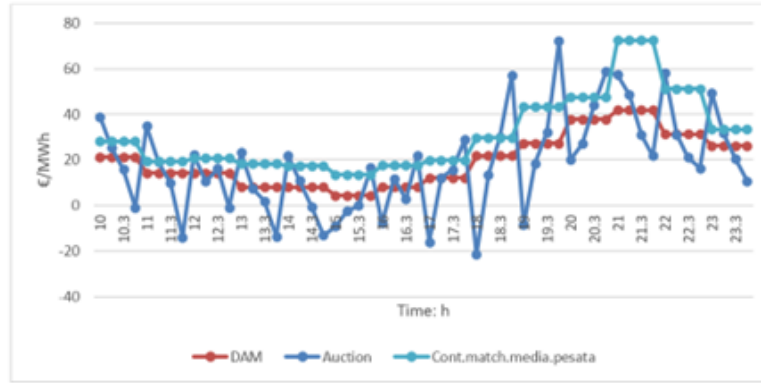


Figure 3.26: Comparison of DAM, ID auction, and hourly ID continuous prices for the same hours from 10 AM to 11 PM on April 15 - H products

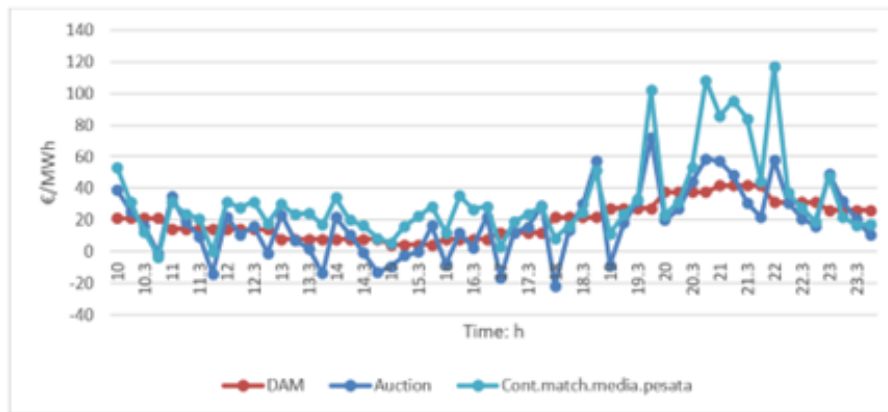


Figure 3.27: Comparison of DAM, ID auction, and quarterly ID continuous prices for hours from 10 AM to 11 PM on April 15 - QH products

It is observed that the prices in the continuous market follow those of the Day Ahead Market (DAM) for hourly products, while they follow the ID auction prices for quarter-hourly products. When analyzing the four different quarter-hours within an auction, significant variability can be observed.

3.5.14 Number of matched offers divided by price ranges

This analysis is conducted over the course of 48 days in a year and presents the density of matched offers with incoming prices based on different price ranges for each market and product. Only one graph is provided out of eight, as they all exhibit a similar pattern to the one shown.

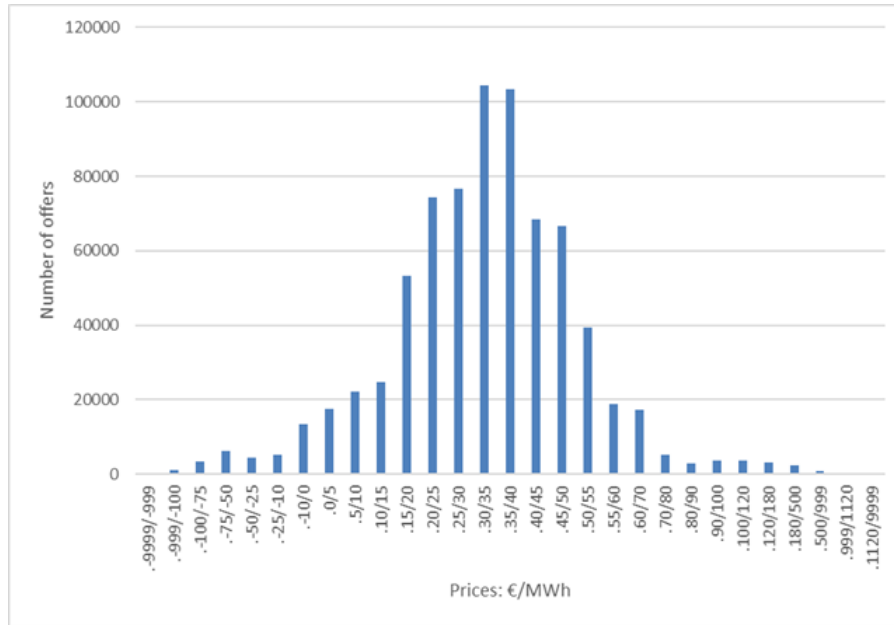


Figure 3.28: Number of matched incoming offers based on different price ranges

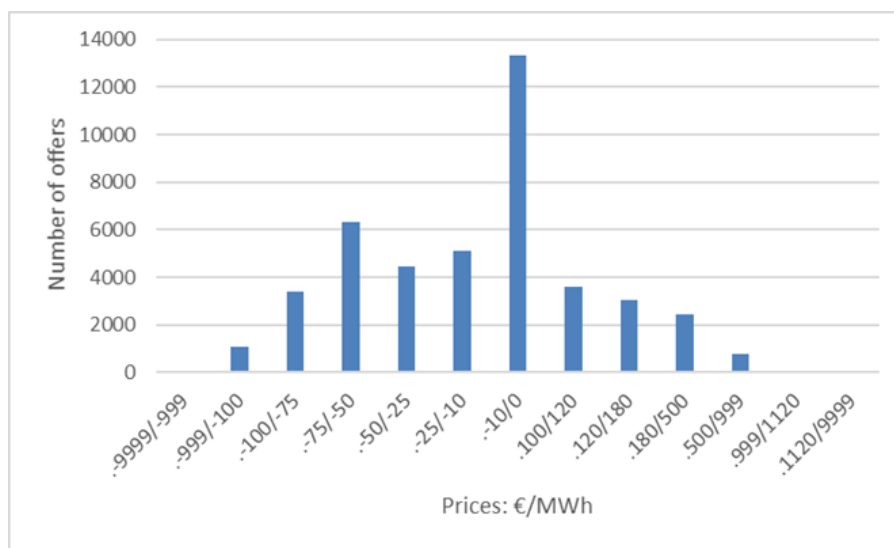


Figure 3.29: Number of matched incoming offers based on different price ranges - Out-liners

It is observed that the majority of orders are presented in the price range of 25-35/40 €/MWh, which corresponds to the average final matching price. Additionally, there is a higher occurrence of orders with negative prices compared to orders exceeding 100 €/MWh. This indicates a trend towards lower prices and potentially negative prices in the market, reflecting market dynamics and factors such as renewable energy generation and supply-demand imbalances.

3.5.15 Percentages of matched orders divided by price ranges

This analysis is conducted over the 48 days of the year and presents the percentages of matched orders categorized by incoming price ranges in different markets and products.

Table 3.11: Percentage of price ranges (€/MWh)

Ranges	% < 0	% > 0, < 100	% > 100
XBID-H-sell	4.5	94.1	1.3
XBID-H-buy	4.9	93.6	1.5
XBID-QH-sell	5.4	93.2	1.3
XBID-QH-buy	5.0	93.6	1.4
ID-H-sell	7.0	91.5	1.4
ID-H-buy	6.8	91.4	1.7
ID-QH-sell	7.0	91.1	2.0
ID-QH-buy	6.3	91.0	2.7

The data indicates that the highest number of orders are matched with prices ranging from 30€/MWh to 35€/MWh, both for hourly and quarterly products. This price range appears to be the most common among the matched orders in the market.

3.5.16 Percentages of matched orders divided by price ranges and by distance from delivery

This analysis is conducted over the course of 48 days in a year and presents the percentages of matched orders categorized into different price ranges and their relation to the distance from delivery.

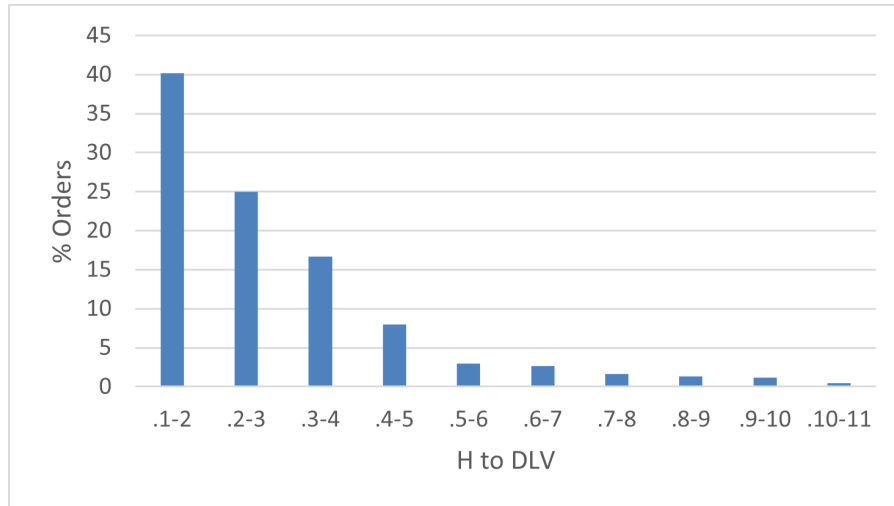


Figure 3.30: Distance (H) from the delivery hour (DLV) for offers with a price range between -10 and 0 €/MWh.

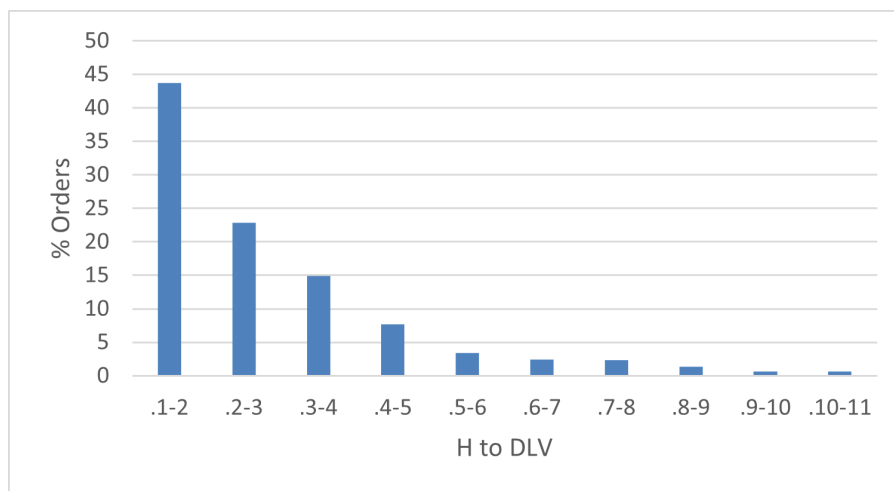


Figure 3.31: Distance (H) from the delivery hour (DLV) for offers with a price range between 30 and 35 €/MWh.

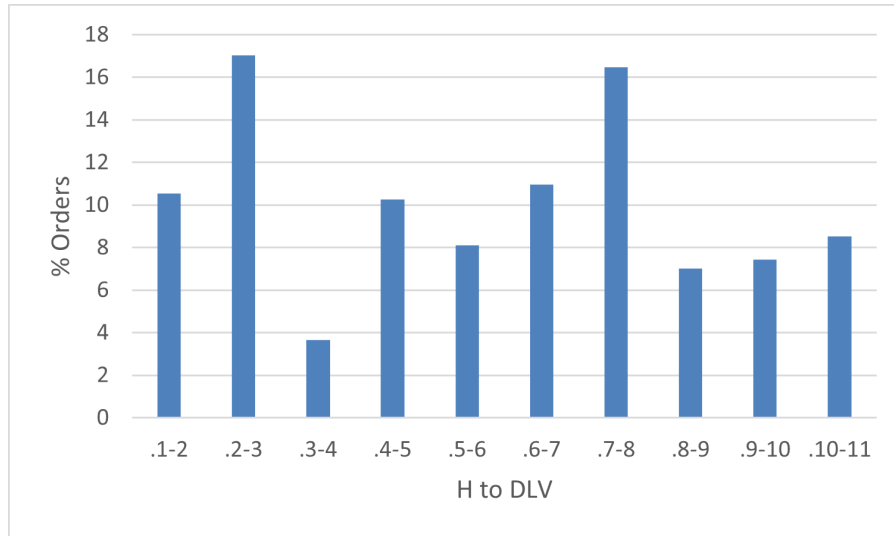


Figure 3.32: Distance (H) from the delivery hour (DLV) for offers with a price range between 180 and 300 €/MWh.

It is observed that based on the various price ranges, 40% of the orders are submitted between the first and second hour prior to delivery, approximately 25% between the second and third hour, and around 15% between the third and fourth hour, with a gradual decrease thereafter. An exception is seen for orders with prices exceeding €200/MWh, as shown in Figure 4-34, which are submitted at various distances from delivery without a distinct trend.

3.5.17 Conclusions on the German intraday market

From the conducted analyses, it can be observed that in the German intraday market, the majority of orders submitted for continuous trading are cancelled by the users themselves, and only a small percentage is actually accepted. In relation to this aspect, an interesting development could be to understand the strategies behind such behavior. As observed in the case of the Iberian ID market, the majority of orders submitted on the XBID platform are of the NON type (orders without any particular restriction) and are mostly submitted approximately 3-4 hours before the delivery. In the German ID market, the possibility of trading up to 5 minutes before the delivery results in the majority of orders being submitted around 30 minutes before the delivery. Consequently, German players logically decide to use the German ID market only for trading energy in the last hour before the delivery (which is not allowed in XBID). In fact, the majority of orders submitted concern the XBID market, where it is possible to have

an accepted order not only with agents belonging to the German market but also with those belonging to the SIDC. Within this market, the most traded products are the quarter-hourly ones, followed by the hourly ones, and only to a lesser extent the 30-minute ones. Analyzing the prices as the distance from the delivery varies, it can be noted that there is a certain uniformity in XBID, whereas in the German ID market, prices often take on very different values as the hourly range varies (the hourly range being only the hour before the delivery, and orders having different prices as the minutes vary). It is likely that orders submitted in the last hour before the delivery (i.e., in the German ID market) serve only to avoid imbalances and do not follow a real strategy or the price signals coming out of the auctions, as is the case in the XBID market. Interestingly, in the continuous market, the prices of the hourly products follow the trend of the prices resulting from the day-ahead market auction, while the prices of the quarter-hourly products follow those of the internal German auction that manages the 15-minute products. In both cases, the prices for accepted offers in the continuous market are slightly higher than those of the two auctions. Analyzing the prices for accepted offers, it is interesting to note that if the price is very different from the prices resulting from the auctions (outliers), there is a greater number of accepted offers at negative prices ($-9999 < \text{price} < 0$) compared to those accepted at high prices (above 100 €/MWh). The majority of accepted incoming orders have prices around 30/40 €/MWh. For all markets, it is observed that, based on the observed data, the lowest prices occur in the month of April, while within a day, low values are observed around the early hours of the day and around noon. The highest prices are consistently recorded towards the evening hours. In conclusion, it appears that even the German market, characterized by the presence of a single auction compared to the six in the Iberian market, maintains good liquidity, and there is no significant price volatility at time intervals distant from the auction. The price signals coming from the day-ahead market and the ID auction are capable of stabilizing the resulting prices in the continuous market around their values. These analyses has been published in [24]

3.6 French market

Similar to Germany, the market operator for France is EPEX Spot [61], and the intraday market consists of both an auction and continuous trading. However, there are notable differences. In France, the auction allows agents to trade only half-hourly products and begins after 17:00 of the previous day. This auction was introduced in 2020, whereas France has been part of the SIDC project since its inception in June 2018. Through the auction, market players can trade within the bidding zones of France, while continuous trading facilitates energy exchange with the rest of Europe. Additionally, France is expected to participate in the LIP14 projects, which involve three pan-European auctions coupled with Italy, Slovenia, Greece, and Austria for intraday energy trading [25]. However, thus far, the three auctions have only been activated for Italy, Slovenia, and Greece, with France’s involvement pending. In 3.12, the structure of the France ID market is illustrated.

Market session	Gate opening	Gate closing	Time horizon	Products
Auction	d-45	17.00 (d-1)	1-24 d	HH
Continuous 1	15.00 (d-1)	d-60'	16.00-24 (d-1), 1-24 (d)	H
Continuous 2	15.30 (d-1)	d-60'	16.00-24 (d-1), 1-24 (d)	HH

Table 3.12: France ID market design

The dataset utilized for our analyses is identical to the data provided for the German market, as it is managed by the common market operator, EPEX Spot.

3.6.1 Number of Matched, Operator Revoked (D), and System Canceled (X) Orders

In the initial analyses, the number of matched orders, orders cancelled by the operator, and orders cancelled by the system were examined. Four months, representing each season, were analyzed, and the results revealed a consistent trend observed in the German market, where the majority of submitted orders are revoked by the agents. This behavior can be attributed to the matching algorithm, which favors the last order entered in the order book, as it has a higher likelihood of being matched with a more favorable order in the opposite direction. Consequently, many agents opt to cancel their orders if an immediate match is not found, as

they perceive a lower probability of achieving a favorable match in the future.

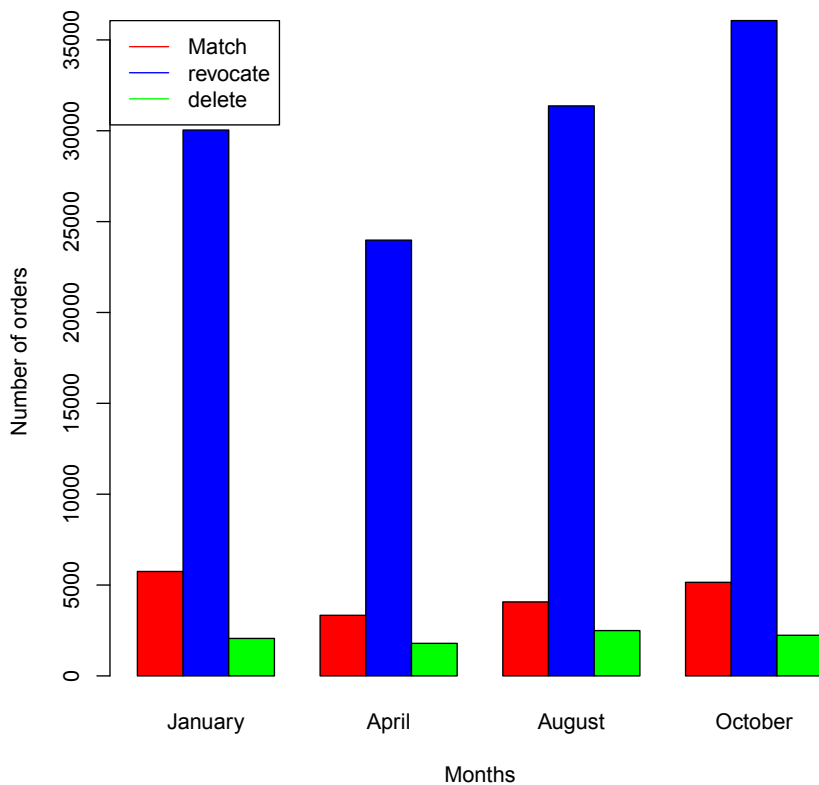


Figure 3.33: Number of orders matched, deleted by the operator and deleted by the system

3.6.2 Percentage of orders submitted, categorized by product type

This analysis focuses on identifying the most prevalent product type in terms of the number of submitted orders. The objective is to determine the preferred product type among agents and assess the level of market liquidity.

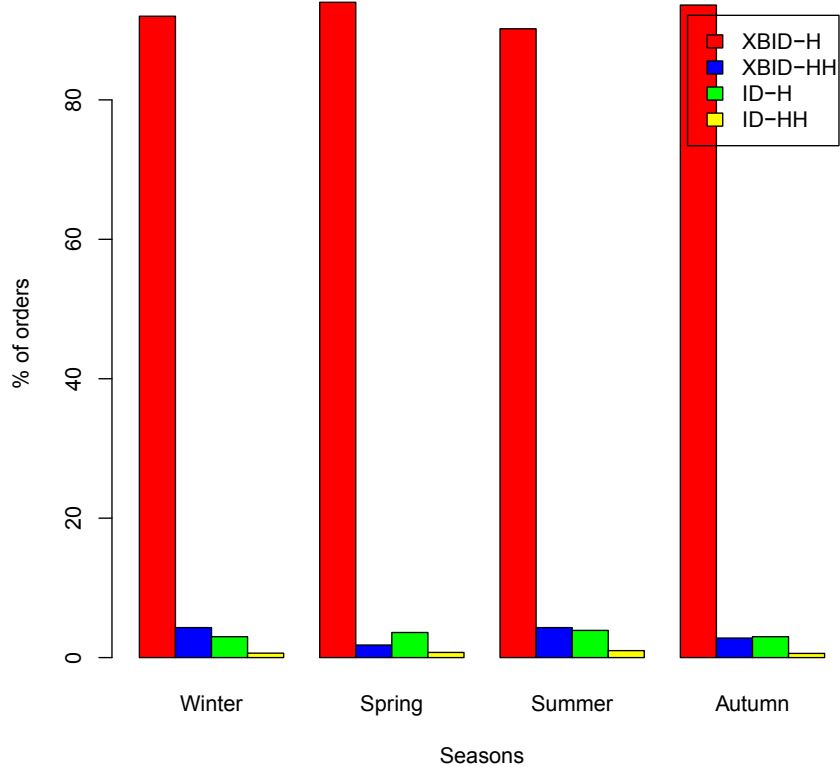


Figure 3.34: Percentage of orders distinguished by product

Figure 3.34 illustrates the distribution of submitted orders throughout the year. The findings indicate that the majority of orders are concentrated in the XBID platform, specifically for hourly products. The internal intraday market attracts less than 10% of the total orders, and the half-hourly product type does not emerge as a dominant choice among agents.

3.6.3 Number of orders categorized by different execution restrictions

In this subsection, the analysis centers on the number of orders that possess execution restrictions, aiming to gain insights into the strategies employed by market players engaged in continuous bidding.

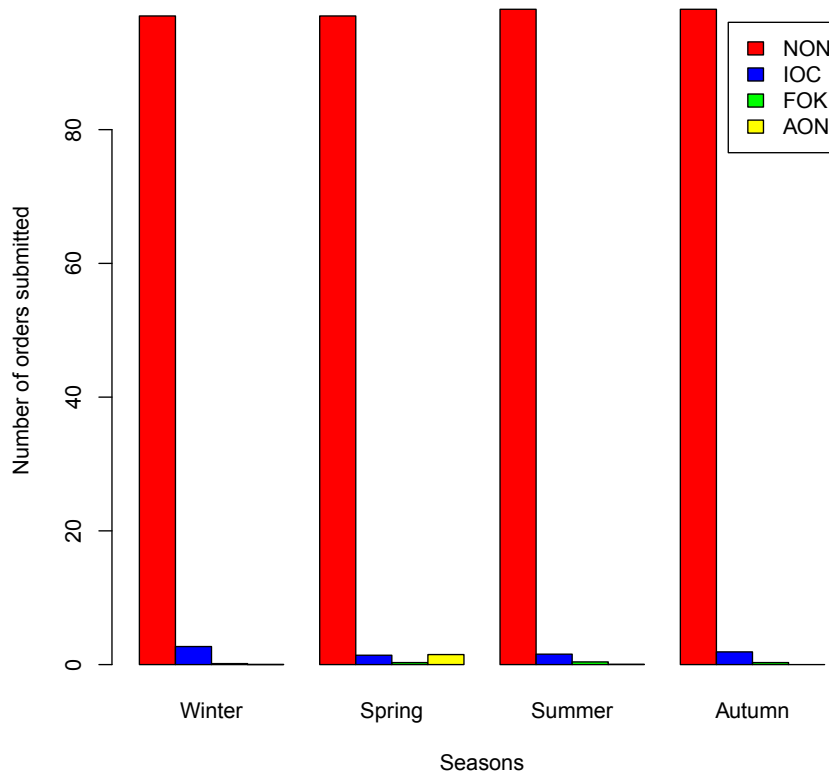


Figure 3.35: Percentage of orders distinguished by product

Figure 3.35 provides a visual representation of the distribution of orders based on their execution restrictions. The results demonstrate that the majority of orders are not subject to any specific restrictions, followed by immediate or cancel orders, while only a small percentage falls under the "all or nothing" category. This observed trend closely aligns with the patterns observed in the German market. The higher proportion of orders without any specific restrictions indicates that market players value flexibility in their bidding strategies. By not imposing constraints on the execution of their orders, they have the freedom to adapt to changing market conditions and adjust their positions accordingly.

3.6.4 Density of orders submitted varying with the hours before the delivery time

The present analysis builds upon the findings presented in Section 3.5.9, which focused on the German market. Figure 3.36 illustrates the probability density function depicting the

distribution of the number of orders submitted, taking into account the temporal gap between their submission and the delivery time.

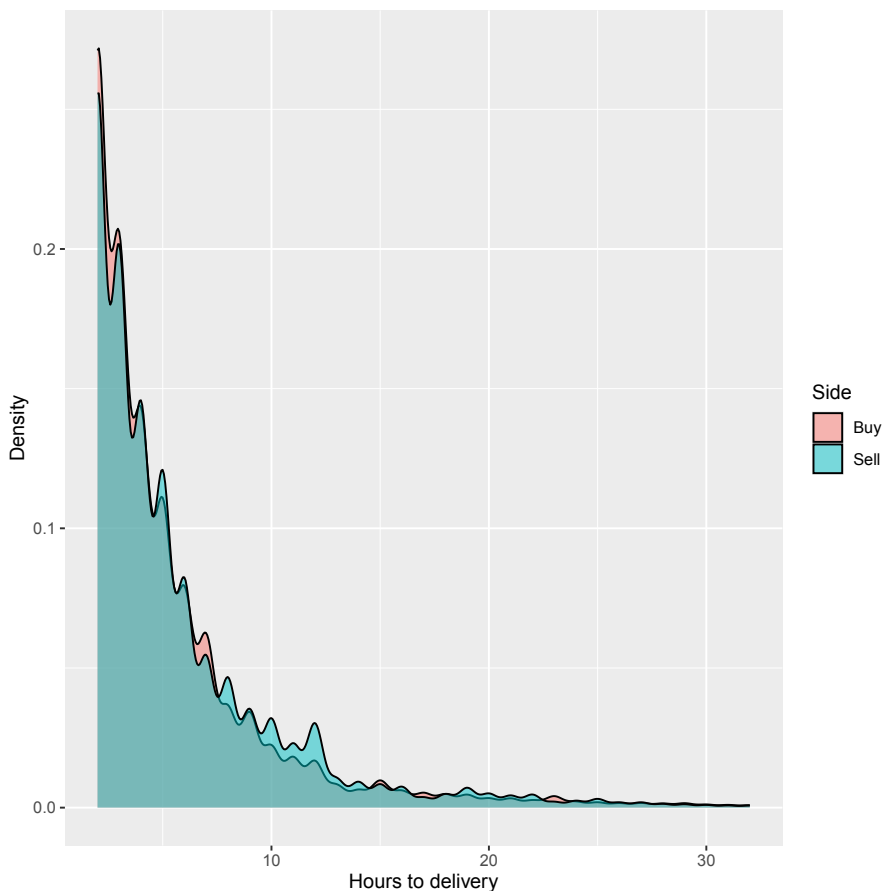


Figure 3.36: Density of orders submitted varying the the hours before the delivery

Similar to the observations made in the aforementioned market, the majority of orders in the French market are submitted in close proximity to the delivery time, with only a small fraction being presented more than 6/7 hours in advance. This indicates a preference among market participants to engage in continuous trading primarily within the last 5 hours available for trading, which is consistent with the pattern observed in other markets.

3.6.5 Mean and median prices of orders submitted and accepted

In this analysis, we aim to examine the price trends of submitted and accepted orders, with a focus on their mean and median values. Figure 3.37 and Figure 3.38 present the prices of orders submitted in four different months of 2020.

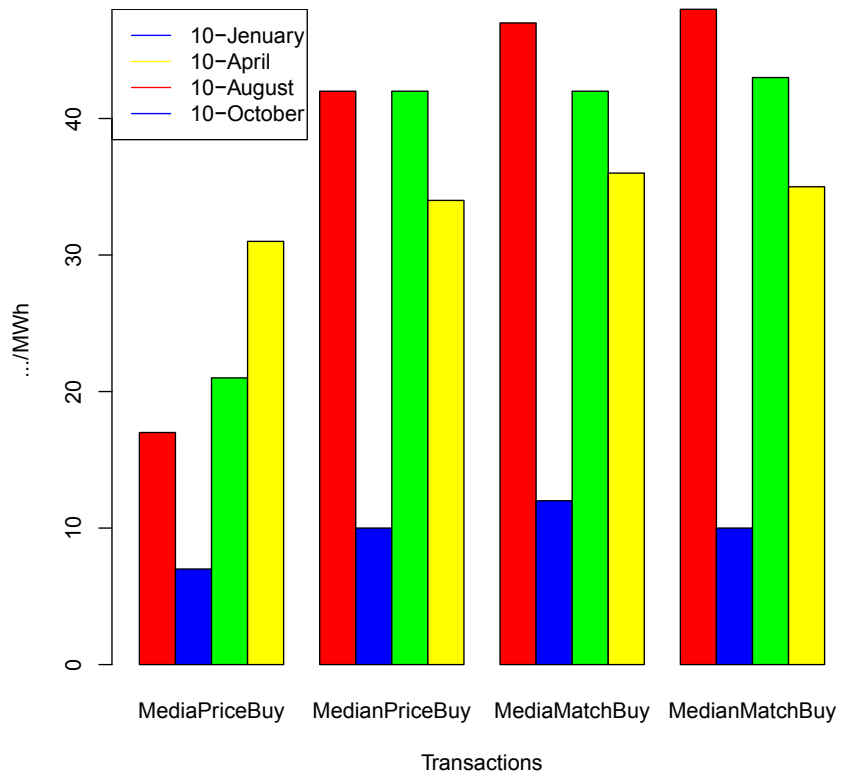


Figure 3.37: Mean and median of buy orders submitted and matched

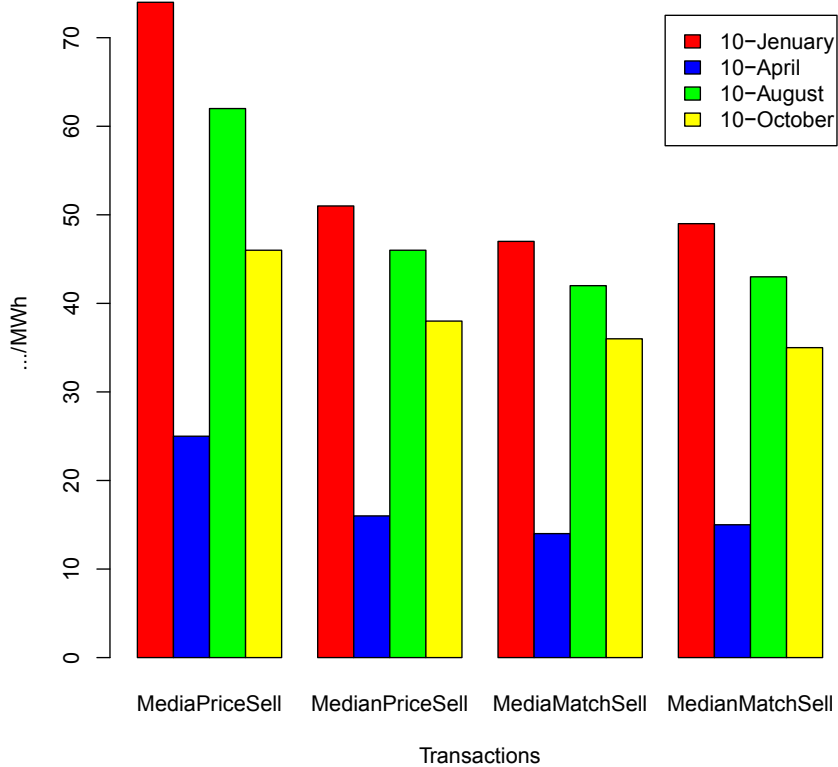


Figure 3.38: Mean and median of sell orders submitted and matched

We observe that the mean price of sell orders submitted is significantly higher compared to the match price, while the mean prices of buy orders submitted are lower in comparison. In contrast, the median prices closely align with the market prices, including for the submitted orders. This finding suggests that the majority of orders submitted during continuous trading are in close proximity to the market price, which is reflected in the match prices. However, it is notable that sellers and buyers still attempt to optimize their revenues and minimize expenses by submitting orders with prices that deviate from the market price. An interesting observation is that bidding at the median of the prices could serve as an effective strategy to achieve a match easily, given its alignment with the market prices.

3.6.6 Trend of matched prices varying the temporal distance between submission and delivery

Figure 3.39 illustrates the relationship between matched prices and the temporal distance between submission and delivery in the continuous intraday market. The figure shows that as the delivery time approaches, the number of matches increases, accompanied by a substantial increase in price volatility.

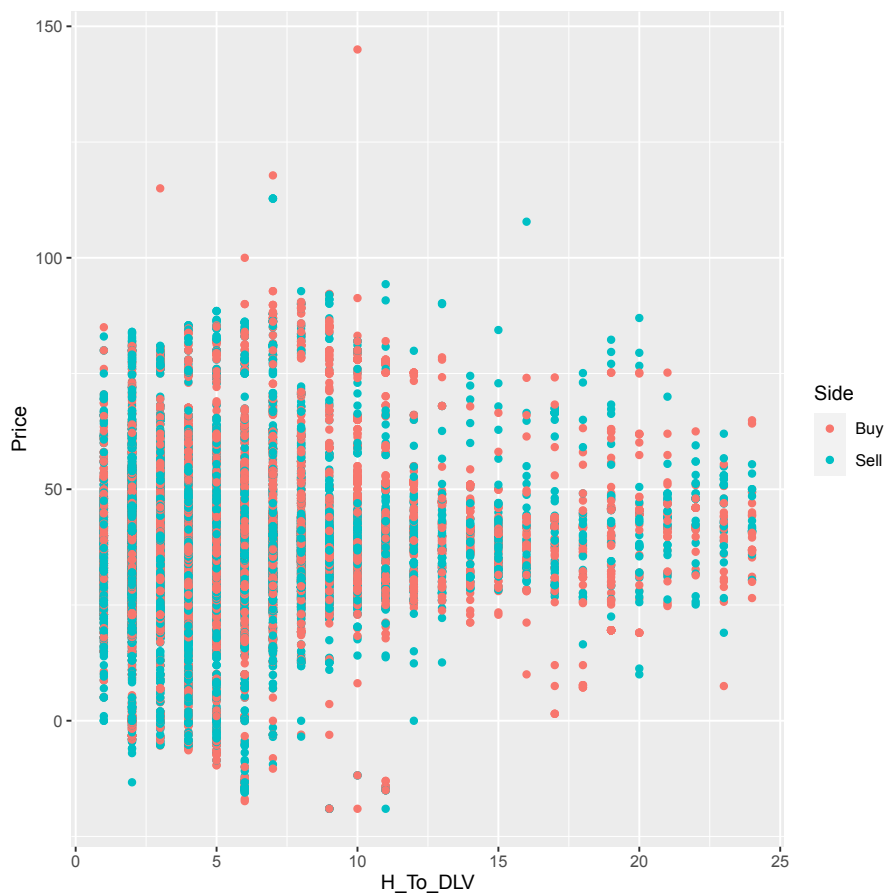


Figure 3.39: Prices of orders accepted considering the temporal distance between the submission and delivery time

This observation is significant as it indicates that as the delivery time nears, market participants tend to submit more orders closer to the prevailing market price in order to secure a match. However, it is likely that there exists a subgroup of agents who submit orders without obtaining favorable returns in their pursuit of finding a match. On the other hand, there may be another subgroup of agents who aim to maximize their revenues by taking advantage of the risk faced by those who risk ending the session with an imbalanced position. This observation

is significant as it indicates that as the delivery time nears, market participants tend to submit more orders closer to the prevailing market price in order to secure a match. However, it is likely that there exists a subgroup of agents who submit orders without obtaining favorable returns in their pursuit of finding a match. On the other hand, there may be another subgroup of agents who aim to maximize their revenues by taking advantage of the risk faced by those who risk ending the session with an imbalanced position.

3.6.7 Trend of submission prices varying the temporal distance between submission and delivery

Figure 3.40 presents the relationship between submission prices and the submission-delivery time in the continuous intraday market. The figure clearly illustrates that buyers tend to submit prices predominantly ranging from the market price to a lower value, while sellers tend to do the opposite by submitting prices predominantly ranging from the market price to a higher value. This pattern holds true across all hours of the day, with no significant variations observed across different time frames.

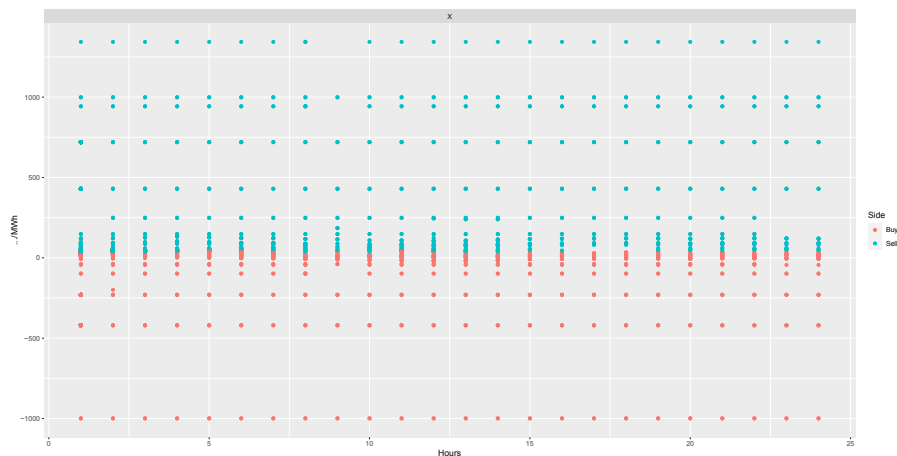


Figure 3.40: Prices of orders submitted considering the temporal distance between the submission and delivery time

This analysis highlights an important finding, complementing the previous analysis. It suggests that agents in the market exhibit a systematic behavior in their price submissions, aligning with their respective roles as buyers or sellers. Buyers aim to secure energy at a price lower than the prevailing market price, whereas sellers aim to sell at a price higher than the

market price. This behavior is consistent throughout the trading hours and indicates a general preference for price deviation from the market price among market participants. Notably, the significance of this observation is reinforced by the previous analysis, which indicated an increase in price volatility during the final hours of the market session. It implies that although agents submit orders with considerable price volatility throughout the day, the highest levels of volatility occur specifically during the closing stages of the market session. This finding emphasizes the critical role of the last hours of the market session, as they witness not only the highest price volatility but also the convergence of buyer and seller strategies. Understanding the dynamics of price submissions and their relationship to market outcomes during these crucial hours can provide valuable insights into the efficiency and stability of the continuous intraday energy market.

3.6.8 Comparison between DAM outgoing prices and ID continuous market matches

In this analysis, we compare the prices derived from the day-ahead market with the matched prices observed during the continuous trading session over a 24-hour period. Figure 3.41 displays the prices obtained from the day-ahead market for each hour of the day, while Figure 3.42 illustrates the corresponding trend in the continuous market.

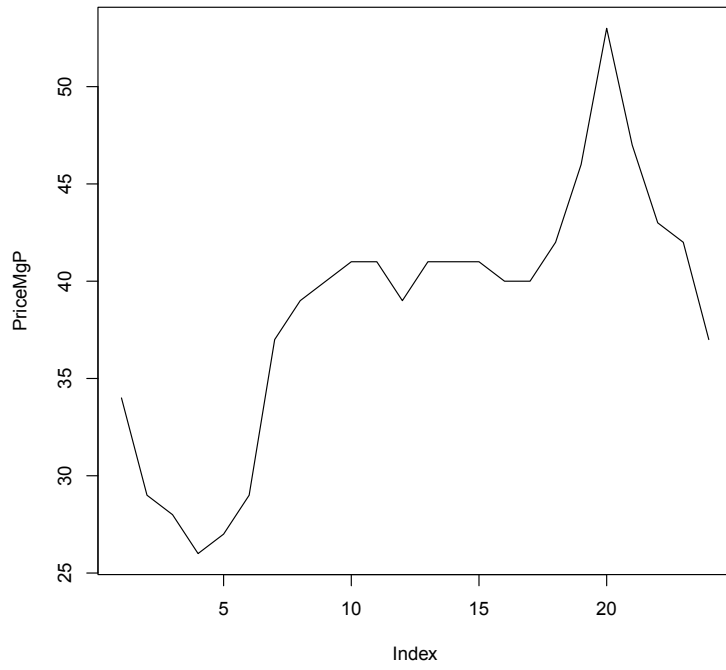


Figure 3.41: Day-ahead market prices of the 10th of August 2020

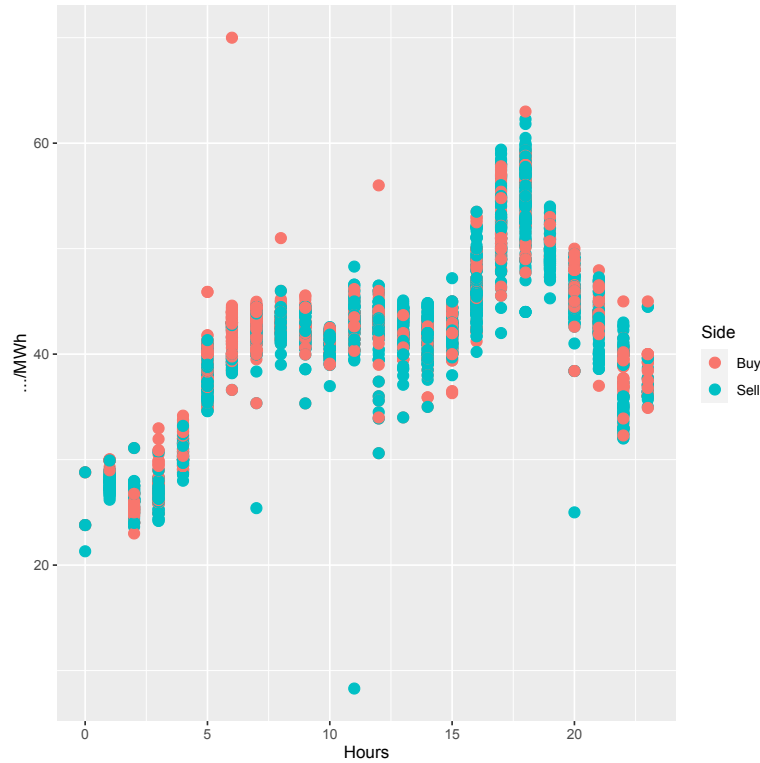


Figure 3.42: Continuous market prices of the 10th of August 2020

The day-ahead market plays a vital role in providing price signals that guide transactions during the continuous trading session. Remarkably, both plots exhibit a similar trend, indicating a close relationship between the match prices observed in the continuous market and the market price determined by the day-ahead auction. The alignment of the two plots signifies that the day-ahead market price serves as an influential reference point for the subsequent continuous trading. Market participants actively respond to this price signal, as evidenced by the spread of the match prices along the market price determined by the day-ahead auction. This finding underscores the importance of the day-ahead market as a crucial mechanism for price discovery and price formation. It also highlights the interplay between the day-ahead and continuous markets, emphasizing the influence of the former on the subsequent trading activities and outcomes in the latter.

3.6.9 Quantity of orders submitted in relations to the delivery time

In the last analysis of the French market, we examine the volume of orders submitted and accepted by market participants in the continuous trading session, considering the temporal

distance between the submission and the delivery time. The corresponding trend is depicted in Figure 3.43.

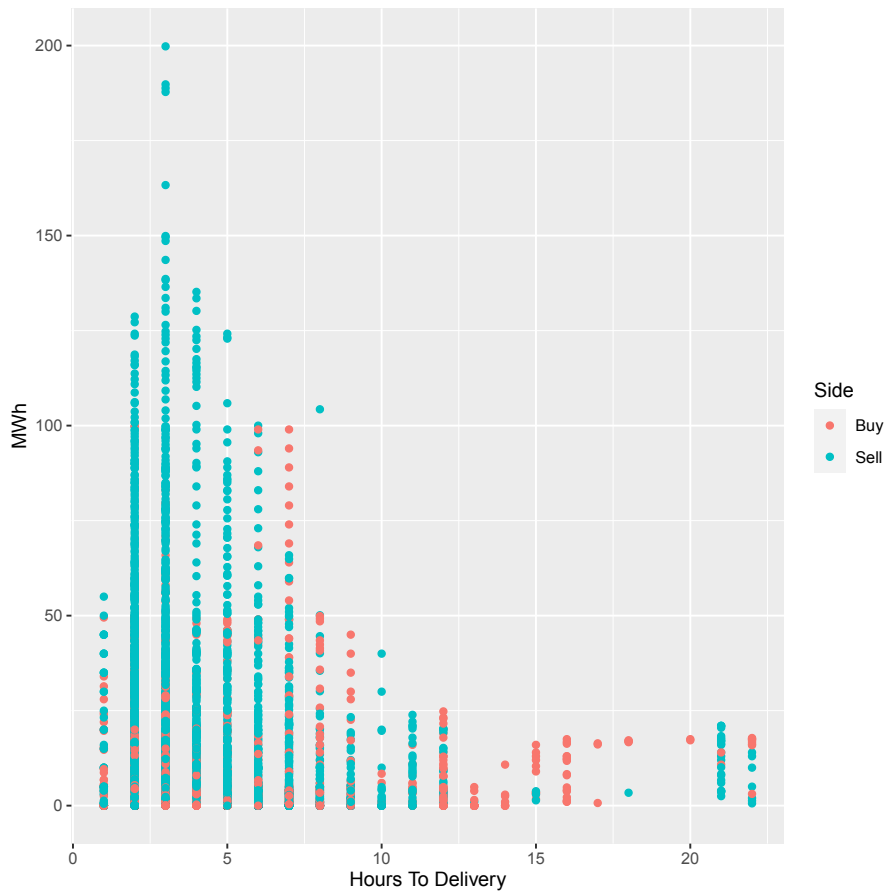


Figure 3.43: Continuous market volumes of the 10th of August 2020

As the delivery time approaches, the volumes of energy submitted exhibit significantly greater variability compared to orders submitted well in advance of the delivery time. This observation implies that market participants tend to adjust their order volumes more dynamically and with larger deviations from the average as the delivery time nears. Interestingly, the analysis reveals that the highest volumes of energy orders are predominantly observed during the last five hours of the market session. Conversely, the quantities of energy orders submitted at the beginning of the session are relatively small in comparison. This finding underscores the time-dependent nature of order volumes in the continuous market. It suggests that market participants tend to adjust their trading strategies and order volumes closer to the delivery time, likely in response to changing market conditions, price signals, and supply-demand dynamics.

3.7 Conclusion on the french market

Based on the analyses conducted for the French energy market, similar trends were observed in comparison to other previously investigated energy markets. Agents within this market appear to employ automated trading systems for order submissions, frequently deleting orders that do not find an immediate match. In fact, a substantial portion of the orders placed in the order book are promptly removed by the agents. Notably, despite the availability of half-hourly products for trading, agents tend to prefer trading on an hourly basis. This preference may stem from the convenience of finding profitable matches, given that the hourly market is integrated with other European markets within the SIDC platform. Similar to the German and Iberian markets, agents predominantly favor the execution restriction known as "NON," which implies no specific restrictions on the order. An interesting observation pertains to the comparison between the mean and median prices. The mean prices for both sell and buy orders differ significantly from the market price, as most agents aim to maximize their revenues or minimize expenses. However, focusing on the median reveals that the median price trend closely aligns with the market price, subsequently influencing the average price of accepted orders. This suggests that agents often place bids at the median price point during continuous trading to facilitate successful matches. Another noteworthy observation concerns price volatility, which exhibits a notable increase during the final hour of the market. This phenomenon can be attributed to two potential factors. Firstly, as the number of orders escalates during this period, it leads to greater price volatility. Secondly, it is plausible that agents seek to maximize their profits during the final hours of the market, recognizing that there are counterparts willing to make substantial purchases to avoid penalties associated with imbalances. In the final analysis, there is a noticeable fluctuation in the volume of traded energy during the last hour of the trading session. Specifically, it appears that agents submit relatively low energy volumes well before the delivery time, potentially to conceal their true energy needs from other participants. However, as the delivery time approaches and a surge in order submissions occurs, energy volumes experience a significant increase, sometimes exceeding 100 megawatt-hours (MWh).

3.8 The coordination with MSD

The coordination between the intraday market and ancillary services market is a multifaceted process in France, Germany, and Spain. In France, the balancing market operates on quarter-hourly market periods, while Germany employs four control areas, each managed by its TSO, and cooperates through the Grid Control Cooperation (GCC). This cooperation includes modules focusing on automatic frequency restoration reserve (aFRR) and aims to reduce counter-acting activations and procure reserves through a common market. Spain's ancillary services market, also known as the deviations management market, comes into play when the predicted generation-demand imbalance exceeds 300 MWh, and these hours are no longer negotiable in the intradaily adjustment market. Only generating units and pump storage units can participate in Spain's market.

The coordination in these countries involves various modules and mechanisms. In France, the market is based on a dual-pricing scheme, where imbalance prices differ based on the direction of the system imbalance (SI). In Germany, the TSOs collaborate for balanced control areas and employ a common merit-order for reserve activation. In Spain, the black-start provision is not remunerated, and there's an emergency energy restoration plan for blackouts. The Spanish system is well-meshed, lowering blackout risks.

Overall, these countries employ different strategies, market structures, and collaboration mechanisms to ensure the effective coordination between intraday and ancillary services markets, adapting to their specific energy landscapes and regulatory frameworks.

Chapter 4

Intraday market in the Italian context

4.1 Italian market

Before delving into the specific aspects of the Italian intraday market structure and its evolution after the implementation of the single intraday market coupling, it is important to understand some general characteristics of the Italian electricity market. In Italy, the Nominated Electricity Market Operator (NEMO) is represented by GME (Gestore dei Mercati Energetici) [62]. GME plays a crucial role in facilitating wholesale energy trading by serving as the central counter-party for both buying and selling energy in the day-ahead and intraday markets. On the other hand, the Transition System Operator (TSO) responsible for the management of the national transmission grid and ensuring the smooth flow of electricity is TERNA [63]. TERNA is responsible for planning, developing, and maintaining the transmission infrastructure. They are also responsible for managing the electricity flow and addressing any congestion issues that may arise. To account for the structural transmission constraints, TERNA has divided the Italian territory into seven distinct bidding zones, namely Northern Italy, Central-Northern Italy, Central-Southern Italy, Southern Italy, Sicily, Sardinia, and Calabria [64]. Market participants have the ability to trade energy across different zones as long as there is sufficient available transmission capacity. The day-ahead market, where electricity is traded for delivery on the following day (referred to as D-1), concludes at 12 a.m. of the day before the delivery. After the closure of the day-ahead market, participants have the opportunity to engage in trading activities during the intraday market. The intraday market allows for the adjustment of energy

positions closer to the delivery time, offering flexibility to market participants. Understanding the roles of GME as the NEMO and TERNA as the TSO, along with the geographical zoning of the Italian electricity market and the sequential timeline of the day-ahead and intraday trading, provides a foundation for comprehending the subsequent aspects related to the Italian intraday market structure.

4.1.1 ID structure before September 2021 – Auction model

Prior to the implementation of the Single Intraday Market Coupling (SIDC), the Italian intraday (ID) market operated through a system of seven implicit auctions known as MI1, MI2, MI3, MI4, MI5, MI6, and MI7 [22]. These auctions enabled market participants to trade energy a minimum of four hours before the delivery time, as detailed in table 4.1. The first three auctions (MI1, MI2, and MI3) took place on the day preceding the actual delivery of energy (referred to as D-1), while the remaining four auctions (MI4, MI5, MI6, and MI7) were conducted on the delivery day itself (D). During these auctions, market participants had the opportunity to submit bids or offers for hourly products, and all accepted bids and offers were financially settled based on a zonal clearing price. Table 4.1 provides information about the structure of the auctions, outlining the specific characteristics and timing of each auction session [62]. This information offers market participants and stakeholders insights into the organization and scheduling of the Italian ID market prior to the introduction of the SIDC.

Table 4.1: Structure of the previous Italian ID market

	MI1	MI2	MI3	MI4	MI5	MI6	MI7
Gate opening	12:55 (D-1)	12:55 (D-1)	17:30 (D-1)	17:30 (D-1)	17:30 (D-1)	17:30 (D-1)	17:30 (D-1)
Gate closing	15:00 (D-1)	16:30 (D-1)	23:45 (D-1)	03:45 (D)	07:45 (D)	11:15 (D)	15:45 (D)
Time horizon	00:00-24:00 (D)	00:00-24:00 (D)	04:00-24:00 (D)	08:00-24:00 (D)	12:00-24:00 (D)	16:00-24:00 (D)	20:00-24:00 (D)
Products available	H	H	H	H	H	H	H

4.2 ID structure after September 2021 – Hybrid model

In September 2021, the Italian electricity market authorities made a significant decision to revamp the existing market structure [65]. This involved the replacement of the previous seven auctions with the introduction of the Single Intraday Market Coupling (SIDC) platform and the

implementation of a continuous trading mechanism. This transformative step was driven by the ACER decision highlighted in Section 1 [66]. Under the new framework, the Italian intraday (ID) market adopted a hybrid model, combining continuous trading with three implicit auctions [67]. This novel approach allows market participants to engage in trading activities until one hour before the real-time period, which coincides with the operation of the national ancillary services market. During the auction sessions, the interconnection capacity is allocated among all Italian bidding zones, as well as other areas interconnected with the Italian territory. It is important to note that the auctions and continuous trading sessions are conducted sequentially and do not overlap. The specific order of the sessions is as follows: MI-A1, continuous session 1, MI-A2, continuous session 2, MI-A3, continuous session 3 [62]. Table 4.2 provides an overview of the new structure of the Italian ID market, capturing the revised arrangement and sequence of the auction sessions and continuous trading sessions.

Table 4.2: Structure of the new Italian ID market

	MI-A1	Continuous session 1	MI-A2	Continuous session 2	MI-A3	Continuous session 3
Gate opening	12:55 (D-1)	15:30 (D-1)	12:55 (D-1)	22:30 (D-1)	12:55 (D-1)	10:30 (D)
Gate closing	15:00 (D-1)	21:40 (D-1)	22:00 (D-1)	H-1/09:40 (D)	10:00 (D)	H-1/13:00 (D)
Time horizon	00:00-24:00 (D)	00:00-24:00 (D)	00:00-24:00 (D)	00:00-24:00 (D)	13:00-24:00 (D)	12:00-24:00 (D)
Products available	H	H	H	H	H	H

Since the implementation of the Single Intraday Market Coupling (SIDC) in Italy, the Italian market has actively participated in the Local Implementation Project 14 (LIP 14). This project facilitated the coupling of the continuous trading and auction sessions with neighboring countries. Specifically, the three intraday auctions in Italy are now referred to as Cross Border Intraday Auctions (CRIDA). These auctions enable the exchange of energy between Italy and Slovenia, Italy and Greece, as well as among the different bidding zones within Italy. Furthermore, in the continuous trading session, Italy is coupled with the same aforementioned countries, along with the bidding zones of France and Austria. This coupling arrangement allows market participants to engage in cross-border trading activities and access a broader pool of potential counterparties. With these two distinct settings in which market agents can compete to address their imbalances, it becomes pertinent to compare the outcomes in terms of prices and volumes. The subsequent chapter will present a detailed analysis of these results, shedding light on the dynamics and performance of the coupled Italian intraday market in both

the auction and continuous trading settings.

4.3 The main innovations

4.3.1 The New IT-COUP Market Zone

In SIDC, the management of interzonal capacities is crucial because the CMM module, interacting with the SOB module, can impact the visibility and subsequent matching of orders. Therefore, the proper management of constraints imposed by the physical power grid is of utmost importance. The need to model the voltage stability and dynamic constraints of the Italian system with "allocation constraints" used by the matching algorithms inherent to SIDC, along with the possibility for TSOs to transmit interconnection constraints to NEMOs, led Terna to communicate to GME the introduction of a new market zone called IT-COUP between the NORD zone and the foreign zones of France, Austria, and Slovenia [68].

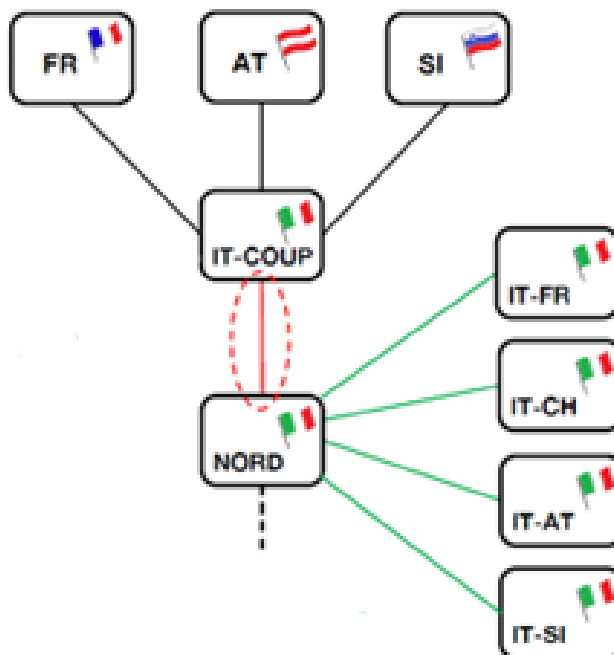


Figure 4.1: New IT-Coup zone

The new zone is effectively used only to set the aforementioned constraints that affect the sum of exchanges with the NORD zone; the foreign virtual zones are only connected to the NORD zone without any limits (see Figure 4.1).

4.3.2 Portfolio Offers and the Nomination Platform

With the introduction of SIDC, the Italian market has shifted from a unit-based trading mode to a zonal portfolio trading mode. Historically, operators were required to specify the individual production or consumption unit when submitting bids on the Day-Ahead Market (DAM) and Intraday Market (MI). The unit bidding approach implicitly determined the unit commitments alongside trading activities.

Under SIDC, operators have the option to engage in zonal portfolio trading, which involves multiple units. This is facilitated through the use of a "nomination platform" that allows operators to explicitly allocate the commercial balance of their zonal portfolios to the corresponding units after the trades have taken place. Without this capability, operators would need to coordinate their bidding strategies with the dispatch constraints of each individual unit during continuous trading, which would be highly complex when dealing with numerous plants without automated trading tools.

Each operator is assigned a portfolio consisting of their available production units. They can choose to refer their offers to the portfolio as a whole (indirectly to all units) or to a specific individual unit. In terms of energy trading limits, if offers are made on a unit basis, the limits will correspond to the upward and downward margins of the specific unit. However, if offers are made on a portfolio basis, the limits will be defined by the sum of the upward and downward margins of all units included in the portfolio. The offers that are matched in the continuous market determine the zonal commercial position for each hour, which is the algebraic sum of all sales (-) and purchases (+) for the zonal portfolio or individual units. For consumption units, a separate commercial position is established as they are not part of any portfolio.

These commercial positions then need to be "nominated," meaning they must be assigned to the respective units through the nomination platform. The nomination phase for each hour "h" closes 57 minutes prior to that hour, at "h-57". If trading was conducted on a unit basis, the nomination will be implicit and automatically attributed to the relevant unit. However, if trading was conducted on a portfolio basis, it is necessary to explicitly nominate the affected units, which must be done by the unit owners. For consumption units, nomination is always implicit.

The nominations are then verified and adjusted based on the corresponding commercial position of the portfolio they refer to (for consumption units, this verification occurs during trading) and the feasibility intervals of the units. Specifically, the imputed nominations must align with the selling commercial position, while the withdrawal nominations must align with the buying commercial position. If a nomination is not verified, it must be rectified through the nomination platform.

4.3.3 The coordination with MSD

In the previous structure of the intraday market and its relationship with the Market System Operator (MSO) Dispatch (MSD), MSD operated to correct the outcomes of the various intraday market sessions to ensure system adequacy and security. However, with the introduction of continuous portfolio trading, MSD can no longer make corrections to these outcomes. This necessitated the identification of a new solution to maintain the current sub-phases of MSD ex-ante and their temporal activations while imposing constraints that represent the boundaries within which market participants can perform the nomination operations [69]. These constraints are referred to as "feasibility intervals" (see Table 4.3).

Table 4.3: Reference programs for MSD

Preliminary nomination (17:00)	MSD 1
Nomination 2 (00:03)	MSD 2
Nomination 6 (04:03)	MSD 3
Nomination 10 (08:03)	MSD 4
Nomination 14 (12:03)	MSD 5
Nomination 18 (16:03)	MSD 6

The new coordination with MSD imposes two obligations on the units:

- Obligation to perform a pre-nomination, before each sub-phase of MSD ex-ante, with the quantities negotiated in continuous trading, as changes made to the results of the last auction;
- Obligation to perform the nomination within the feasibility intervals.

The coordination among the various market sessions in Italy underwent a transition from the structure depicted in figure 4.2.

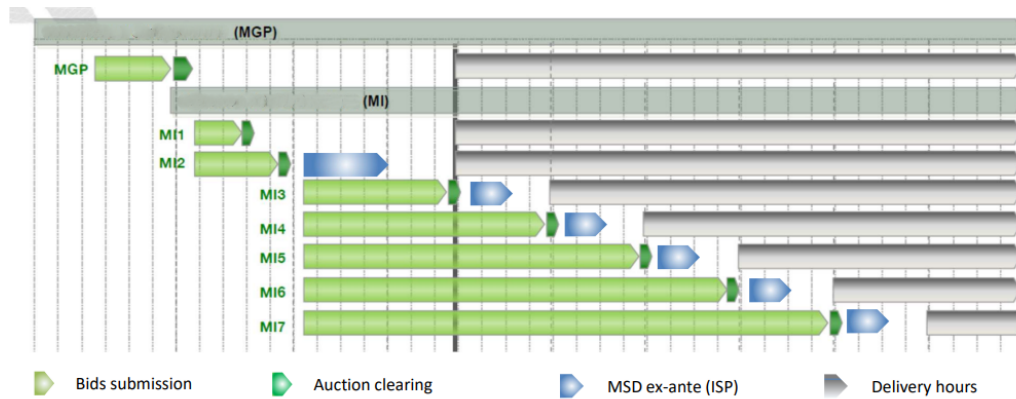


Figure 4.2: Past intraday and integrated scheduling process

To the one illustrated in figure 4.3

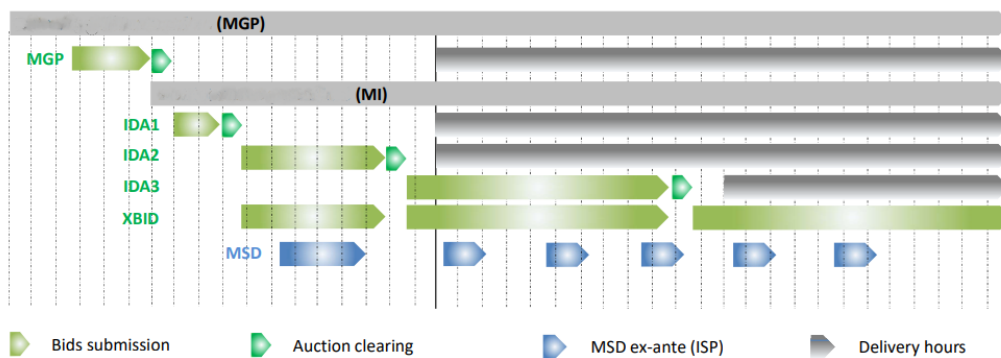


Figure 4.3: New intraday and integrated scheduling process

With the new scheduling, a complete coordination between the Intraday market and the ancillary services market (MSD) is no longer necessary. Instead, only partial reconciliation between the two mechanisms is required.

4.3.4 CRIDA

In the regional context of interest for Italy, the network operators (TSOs) and market operators (NEMOs) of Italy, France, Austria, Slovenia, and Greece have proposed the implementation of complementary regional intraday auctions, called CRIDA (Complementary Regional Intraday Auction), starting from 2016. This proposal aims to reconcile the continuous trading mode with auctions for cross-border capacity allocation. The CRIDA auctions provide the intraday market with price signals for inter-zonal capacity and allow for the extraction of congestion rents resulting from capacity allocation. Currently, CRIDA auctions cover the internal zones of

Italy, Greece, and Slovenia, while France and Austria will introduce intraday auctions directly. Figure 3-4 shows the connections between the different internal zones of the Italian market, along with the connections with Slovenia and Greece where energy exchanges occur in the intraday market.



Figure 4.4: Network model used by CRIDA between Italy, Slovenia, and Greece

The number and timing of these CRIDA coincide with those of the future pan-European IDAs, scheduled to begin in 2023, making them a sort of preview. The capacities involved in the three auctions are:

- First auction: remaining capacity of DAM.
- Second auction: capacity available after the first calculation process, i.e., the remaining capacity after exchanges in the first auction and continuous trading (IDCC1, expected by the end of 2022).
- Third auction: capacity available after the second calculation process, i.e., the remaining capacity after exchanges in the second auction and continuous trading (IDCC2).

During each auction session, the continuous market is suspended for 50 minutes, and it is not possible to allocate any capacity in the SIDC.

4.4 Statistical analyses

4.4.1 Sources

The analyses conducted in this study utilized data obtained from the Italian Nominated Electricity Market operator (GME), which serves as the central repository for storing all information related to transactions in the Italian electricity market. This comprehensive data-set includes detailed records of prices and volumes for various market activities. Specifically, the study considered two sets of results for comparison. Firstly, the volumes and prices associated with the seven auctions that characterized the previous intraday (ID) market design were examined. These auctions were part of the earlier market structure and operated independently. Secondly, the study analyzed the outcomes of the current ID market design, which combines continuous trading with three implicit auctions. The data encompassed both the continuous trading sessions and the three sequential implicit auctions. By comparing these results with the previous auction-based market structure, a comprehensive evaluation of the market's performance under the new design was conducted [22].

4.4.2 Analyses classification

In this next sections, historical data of the Italian ID market are analyzed throughout statistical analyses of prices and volumes gathered before and after September 2021 (October 2020, 2021 and 2022). This lead to investigate how agents have changed their behavior in front of two ID different market models as well as to compare the liquidity and the price volatility (that measure the uncertainty of prices) of the new ID model with the previous scheme.

4.4.3 volumes of energy exchanged

In this analyses the volumes of energy exchanged in October 2020, October 2021, and October 2022 in the different session of the ID market for each Italian bidding zone are presented.

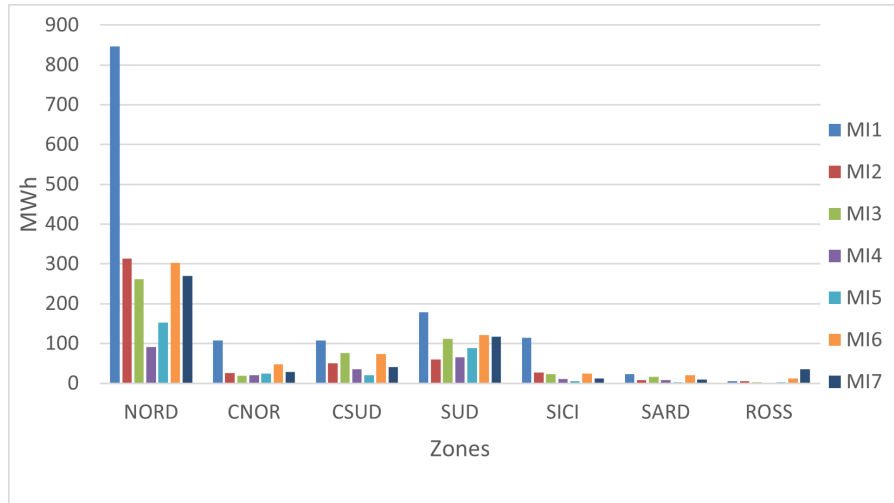


Figure 4.5: Volumes exchanged in October 2020

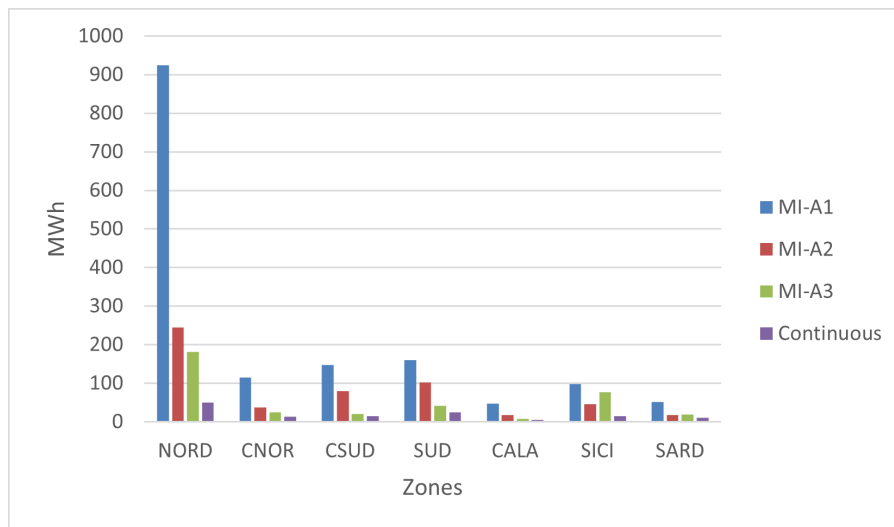


Figure 4.6: Volumes exchanged in October 2021

The analysis of the plots reveals a consistent pattern in the volume of energy purchased throughout the different sessions of the market. It is evident that the majority of energy volumes are transacted during the first auction, indicating that this session is the most liquid and actively participated in. As subsequent sessions progress, the volume of energy traded decreases steadily, reaching its lowest point during the continuous trading session. This observed trend is particularly pronounced during October 2021 (Figure 4.6). This may be attributed to the fact that market participants are still adjusting to the new market structure and may prefer to rely on the familiarity of the first auction to exchange energy, similar to their previous trading behavior. This phenomenon has been documented in the Iberian market as well when it became part of the SIDC platform in 2018. The initial period of transition to a new market

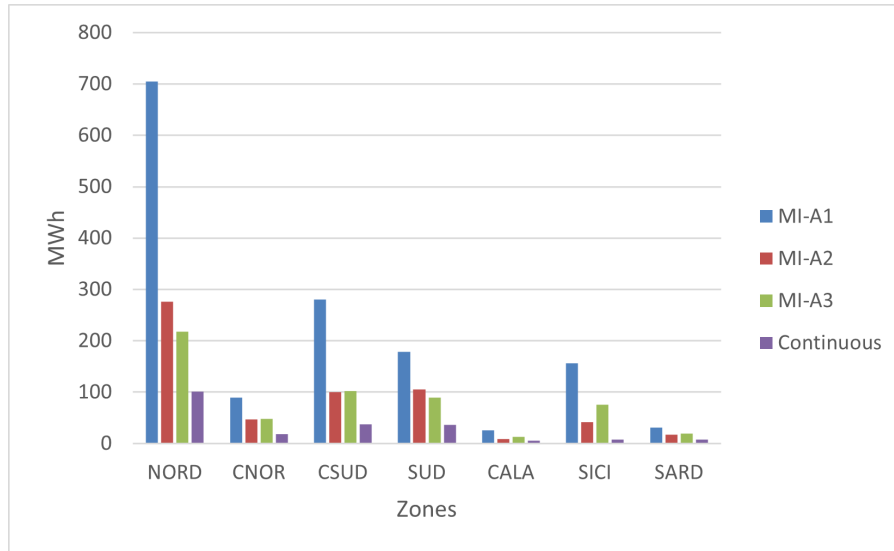


Figure 4.7: Volumes exchanged in October 2022

framework often results in a preference for established trading sessions. Additionally, Figure 4.7 provides further insights into the behavior of market agents. It illustrates that participants begin trading larger volumes during the subsequent sessions of the market. This may be due to their growing familiarity and practicality in engaging in trades closer to the real-time delivery period. As market participants become more accustomed to the new market structure and gain confidence in trading closer to the delivery time, they are likely to increase their volumes in these later sessions.

4.4.4 Volumes exchanged in continuous

Focusing on trading in continuous, Figures 4.8 and 4.9 2 shows the variation of volumes exchanged continuously in all bidding zones in October 2021 and October 2022.

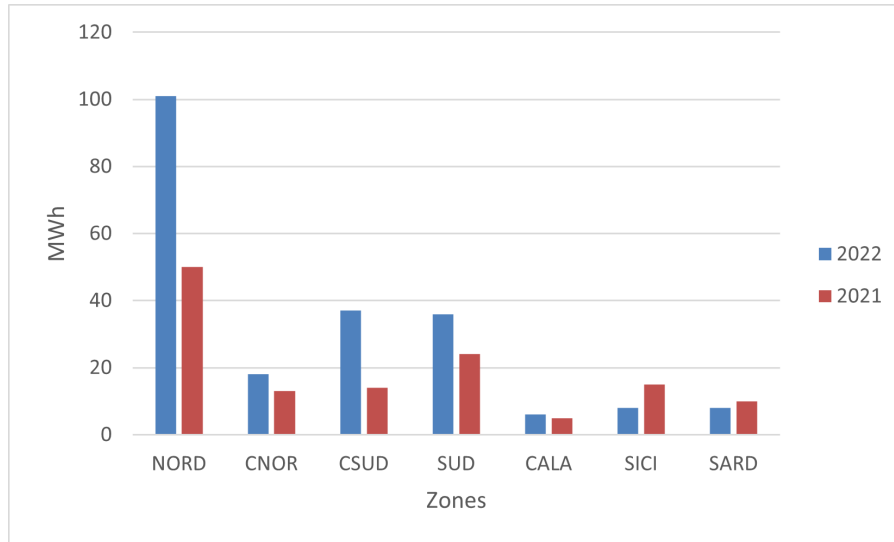


Figure 4.8: Volumes sold in continuous

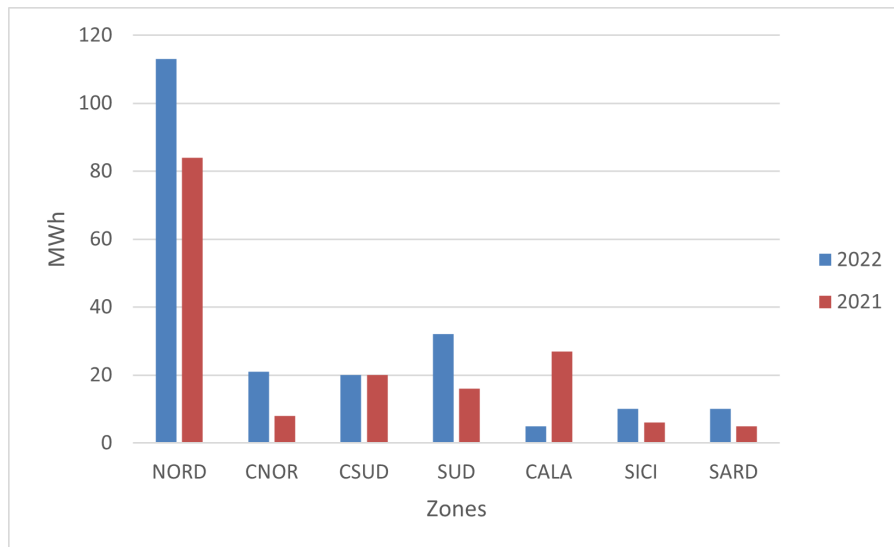


Figure 4.9: Volumes purchased in continuous

The analysis of trading volumes in the continuous session reveals a notable trend across almost all bidding zones. Specifically, one year after the introduction of the Single Intraday Market Coupling (SIDC), both buyers and sellers have witnessed an increase in the volumes traded during the continuous session. This observed increase in trading volumes is particularly significant as it indicates the growing participation of solar and wind power plants in the market. These renewable energy sources are becoming more actively engaged in the market due to the advantage of being able to trade energy until just one hour before the delivery time. This flexibility allows solar and wind power plant operators to optimize their trading strategies based on real-time supply and demand dynamics.

4.4.5 Comparison between DAM outgoing prices and ID prices

In the second analyses, how the price strategy formulation has changed after the SIDC market is investigated. To do that, the analyses of trend prices from the day-ahead market until all session of the ID market for the 24 hours of the same day in October 2020, 2021, and 2022 has been carried out. Results are displayed in Figures 4.10 4.11 and 4.12

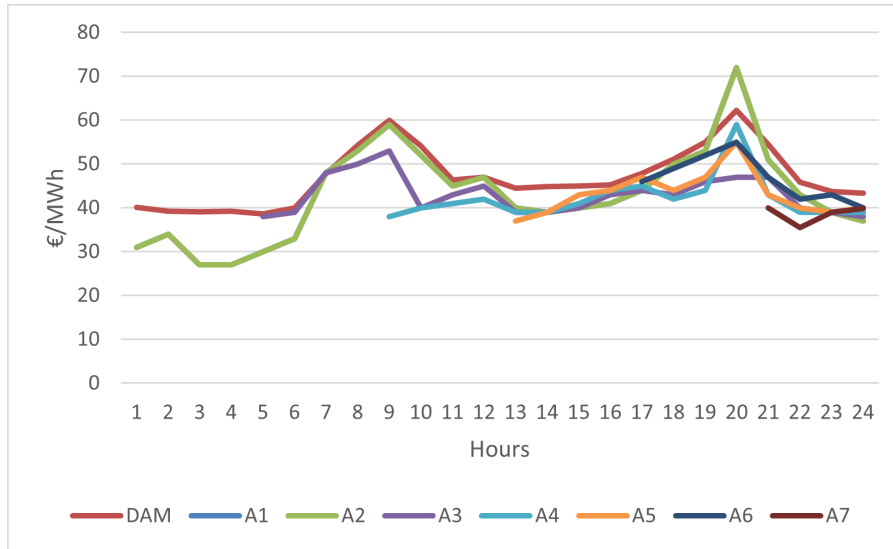


Figure 4.10: trend of prices for the 20/10/2020

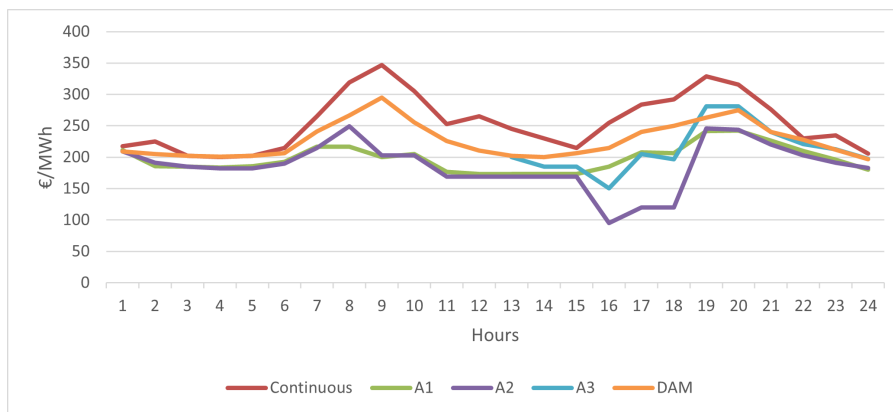


Figure 4.11: trend of prices for the 19/10/2021

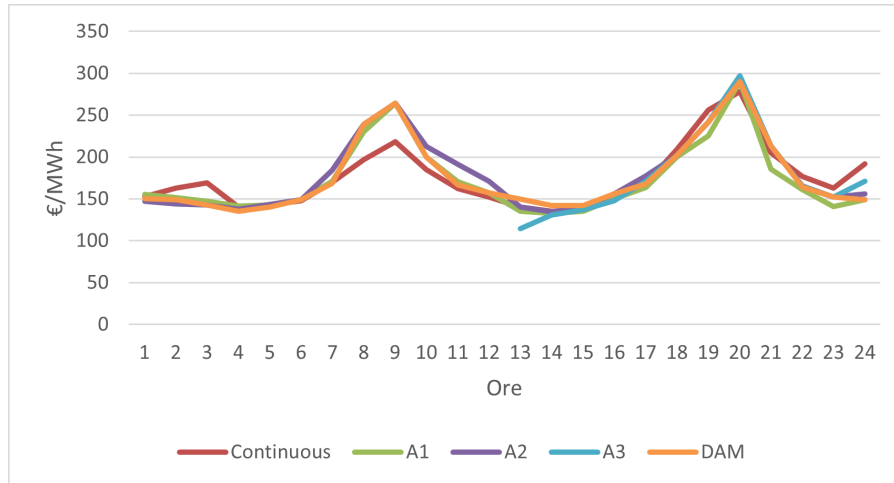


Figure 4.12: trend of prices for the 21/10/2022

The analysis of the plots provides valuable insights into the price dynamics of the intraday (ID) market, particularly in relation to the day-ahead market. In Figure 4.10, it is evident that the prices in the ID market closely align with the prices determined in the day-ahead market, indicating a strong correlation between the two. Furthermore, the volatility of prices in the ID market during this period is relatively low. However, following the introduction of the Single Intraday Market Coupling (SIDC) market, as depicted in Figure 4.11, a significant variation in prices across different sessions of the market is observed. This suggests that market participants may be attempting to maximize their profits or minimize their expenses by submitting offers and bids at different price levels, seemingly without a specific strategy. As a result, the prices resulting from the Cross Border Intraday Auctions (CRIDA) differ from one another, indicating a lack of clear understanding among players on how to effectively utilize continuous trading to purchase energy. Consequently, transaction values experience a significant increase. Comparing the trend depicted in Figure 4.11 with Figure 4.12, which represents the market behavior after one year of utilizing the new SIDC mechanism, it becomes evident that players have become more adept at trading in the SIDC market, intelligently interpreting the price signals provided by the day-ahead market. This improved understanding and ability to strategically engage in the market leads to increased liquidity, as market participants are better able to estimate the offers that need to be submitted to secure transactions. Additionally, non-dispatchable agents, such as renewable energy generators, can efficiently utilize continuous trading to manage their energy portfolios.

4.5 Conclusions

The analysis conducted indicates that auctions continue to be the primary mechanism utilized by market participants for trading in the intraday (ID) market. However, with the implementation of the Single Intraday Market Coupling (SIDC) project, continuous trading has witnessed an increasing level of utilization by market participants each year. This trend can be attributed to the growing presence of renewable energy sources in the market landscape and the need for market participants to respond swiftly to external events. Nevertheless, it is important to note that auctions still play a crucial role in maintaining market liquidity and mitigating price volatility that may arise during continuous trading. The match prices observed in continuous trading align with the prices determined in both the day-ahead market auction and the intraday auctions. This indicates that successful integration of auctions and continuous trading in the new design of the Italian ID market has enhanced market efficiency. It has also facilitated a greater penetration of renewable power plants into the system, as market participants are able to adjust their positions closer to the delivery time, thus enabling more effective risk management. By combining auctions and continuous trading, the revised market structure has achieved improved liquidity and reduced price volatility. This outcome has been beneficial for the integration and expansion of renewable energy sources within the market. The flexibility provided by the SIDC project allows market participants, particularly those involved in renewable energy generation, to adapt their trading strategies and respond to changing market conditions promptly. Overall, the analysis highlights the successful synergy between auctions and continuous trading in the new Italian ID market design. This synergy has led to enhanced market efficiency, increased liquidity, and a more favorable environment for the integration of renewable energy sources. The ability to adjust positions closer to the delivery time has provided market participants with greater flexibility and improved risk management capabilities, ultimately contributing to a more stable and resilient energy market. These considerations have been published in [22]

4.6 Statistical Insights and Strategies for Continuous Trading in Renewable Energy In the Italian context

This sub-chapter provides a comprehensive analysis of the intraday market, investigating the key characteristics and behaviors exhibited by various market players engaged in continuous trading focusing on the bid strategy [70]. The study employs a range of statistical analyses, including density analysis of submission patterns over time, regression analysis, time-series analysis, and correlation analysis to examine the relationship between the prices of submitted orders and the trend price in relation to the day-ahead market. The findings from these analyses are thoroughly explored and discussed. Additionally, the chapter proposes a novel strategy that optimizes expected revenues by considering the probability of achieving a successful match. This strategy aims to assist market participants in maximizing their profits while ensuring a reasonable likelihood of finding a suitable trading partner. Overall, this work contributes to a comprehensive understanding of the European intraday market, with a particular focus on continuous trading. Results has been published in [26]

4.7 Analyses developed

This section details the statistical analyses that were conducted on historical orders

4.7.1 Probability density analyses

To study the probability distribution of orders submitted in relation to the temporal distance between submission and delivery time, a probability density function was created [71]. This function provides a relative likelihood that the value of the random variable would be equal to a given sample at any point in the sample space. [72]. So, A variable X has density f_x :

$$P[a \leq X \leq b] = \int_a^b f_X(x) dx \quad (4.1)$$

The probability density function for the order submission in relation to the delivery time-frame is represented by a non-negative Lebesgue-integrable function f_x , where X is the event

corresponding to the order submitted related to the delivery time-frame. As the events are independent and there are only two possible outcomes (order submitted or order not submitted), a geometric distribution was used for this analysis. The probability of finding the event X after k independent trials can be expressed as:

$$P[X] = (1 - p)^{k-1}p \quad (4.2)$$

Where p is the probability of a successful event.

4.7.2 Correlation analyses

Another analysis was conducted to study the correlations between the prices resulting from the day-ahead market session and the average and median prices of continuous trading order submissions. As the data prices follow a curvilinear and monotonic trend, the Spearman correlation [73] coefficient was used to identify a relationship between the day-ahead prices and the price orders submitted by the market operators into the ID continuous market. The Spearman correlation formula can be expressed as:

$$Cor = \frac{\sum_i (r_i - \bar{r})(s_i - \bar{s})}{\sqrt{\sum (r_i - \bar{r})^2} \sqrt{\sum (s_i - \bar{s})^2}} \quad (4.3)$$

Where r and s are the two parameters to be correlated.

4.7.3 Time-series analyses

This analysis focuses on the time series pattern of data to assess the price trend of the continuous market [74]. Specifically, it was applied to the prices of orders submitted by players with different technologies as the delivery time approached. The aim of this analysis is to highlight the strategies adopted by different market operators when bidding during the continuous trading market. Since the only variable considered is the price over time, the analysis follows the formula:

$$Y_i = \beta_0 + \beta_1 X_i + \epsilon_i \quad (4.4)$$

where β_0 is the intercept, β_1 is the slope coefficient (representing the change in Y for a one-unit change in X), X_i is the independent variable (i.e. time period), Y_i is the dependent variable (i.e. price), and ϵ_i is the error term. The regression analysis estimates the values of β_0 and β_1 that minimize the sum of the squared errors between the predicted values and the actual values of Y . This can be used to understand the relationship between the two variables and make predictions about future price changes based on changes in the independent variable.

4.7.4 Regression analyses

To study the relation between the orders price over time, a regression analyses has been used. Regression models can be applied to predict price changes over time based on various factors, such as weather patterns or economic indicators. The independent variable is the time period between the submission and the delivery of an order and the dependent variable is the price. Calling Y_i the dependent variable and X_i the independent one, the regression model is:

$$Y_i = f(X_i, \beta) + e_i \quad (4.5)$$

$f(X_i, \beta)$ is a function that most closely fits the data, e_i is the error term that is not directly observed in order to investigate the relationship between the price of orders over time, a regression analysis was conducted. Regression models are commonly used to forecast changes in prices over time, taking into account a range of factors including economic indicators and meteorological patterns. The independent variable in this study was the duration between the submission and delivery of an order, while the dependent variable was the price. The regression model took the form of $Y_i = f(X_i, \beta) + e_i$, where Y_i represents the dependent variable, X_i the independent variable, and β the coefficients that determine the relationship between the two variables. The function $f(X_i, \beta)$ was used to identify the best fit for the data, while e_i referred to the error term that could not be directly observed in the data

4.8 Results

The present section reports the outcomes of the statistical analyses conducted. The analyses focused on two specific days of the year 2022, namely October 20 and April 10, and although other days were examined, the results obtained from these two days are deemed to be sufficiently significant to depict the general behavior of the market and the players. The analyses mainly explored the time at which orders were submitted and the trend of prices, with the aim of identifying the strategies adopted by market operators.

4.8.1 Orders submissions

The density function described in section 4.7.1 identifies the preferred time frame for continuous trading by market agents. Figure 4.13 illustrates the relationship between the density of submitted orders (y-axis) and the time-distance (x-axis).

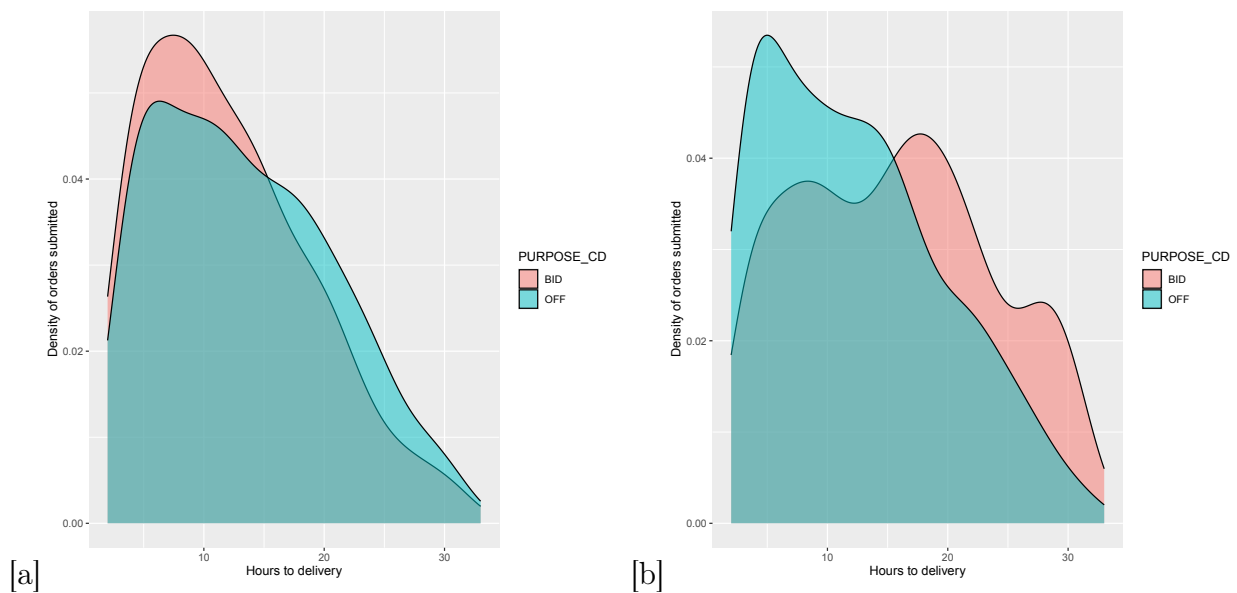


Figure 4.13: Density of orders submitted during the 10 of April 2022 (a) and the 20 October 2022 (b) in relation to the distance between the submission and the delivery time

The plotted density curves of bids and offers exhibit a unimodal and right-skewed distribution, except for bids submitted in October. This indicates that the majority of orders are submitted near the delivery time, while only a small proportion are submitted more than 10 hours in advance. The peak of the curve occurs approximately 4-5 hours before the delivery time, which corresponds to the most liquid period of the trading. As such, market agents seeking to balance

their position before the market session concludes are inclined to trade during the last hours of the trading period.

4.8.2 Price trend

Following the identification of the optimal time-window for order submissions, the subsequent analysis centers on the energy prices associated with those orders. In particular, Figure 4.14 illustrates the daily price trend of the day-ahead market auction alongside the mean and median prices of orders submitted during continuous trading.

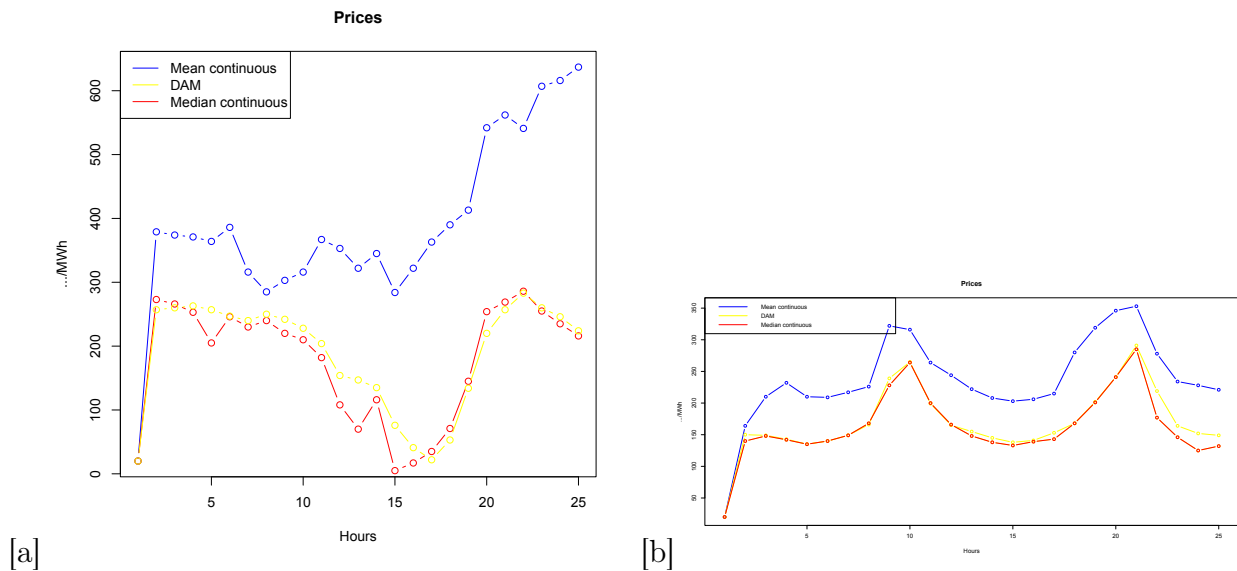


Figure 4.14: Day-ahead, mean continuous and median continuous price trend for the 10 of April 2022 (a) and the 20 October 2022 (b)

The price trend during continuous trading follows an upward trend similar to that observed during the day-ahead market auction. As a result, the mean prices of orders submitted during continuous trading are consistently higher than those of the day-ahead prices. The median prices, which closely track the day-ahead prices, indicate that market participants take cues from the day-ahead market prices and bid accordingly during continuous trading. While some market participants may seek to maximize profits by submitting orders with high prices, it is more advantageous to submit orders close to the day-ahead auction prices to increase the chances of finding a positive match and earning good revenues. Conversely, submitting orders with significantly higher or lower prices reduces the likelihood of a positive match and thus

reduces potential revenues. In figure 4.14 the mean prices of continuous trading do not always follow the dam prices as the media values do. In table 4.4 and 4.5 the correlation values are reported for the day ahead, the mean continuous and median continuous prices are reported.

	Day ahead	Average continuous	Median continuous
Day ahead	1	0.88	0.88
Average continuous	0.88	1	0.81
Median continuous	0.88	0.81	1

Table 4.4: Correlation prices for the 20 October 2022

	Day ahead	Average continuous	Median continuous
Day ahead	1	0.32	0.88
Average continuous	0.32	1	0.54
Median continuous	0.88	0.54	1

Table 4.5: Correlation prices for the 10 April 2022

The sole robust correlation observed is consistently between the median and the day-ahead market prices. This emphasizes the potential for studying the continuous trading price submission average to misrepresent the true price trend and mislead the formulation of agent prices.

4.8.3 Prices in relation to the delivery time

It is essential to examine the price trend with respect to the time gap between the submission and delivery times. Figure 4.15 illustrates the time series of submission prices (Price S.) and transaction prices (Price T.) as the delivery time (H to DLV) approaches for four distinct power plants, namely, solar, wind, hydro and thermal.

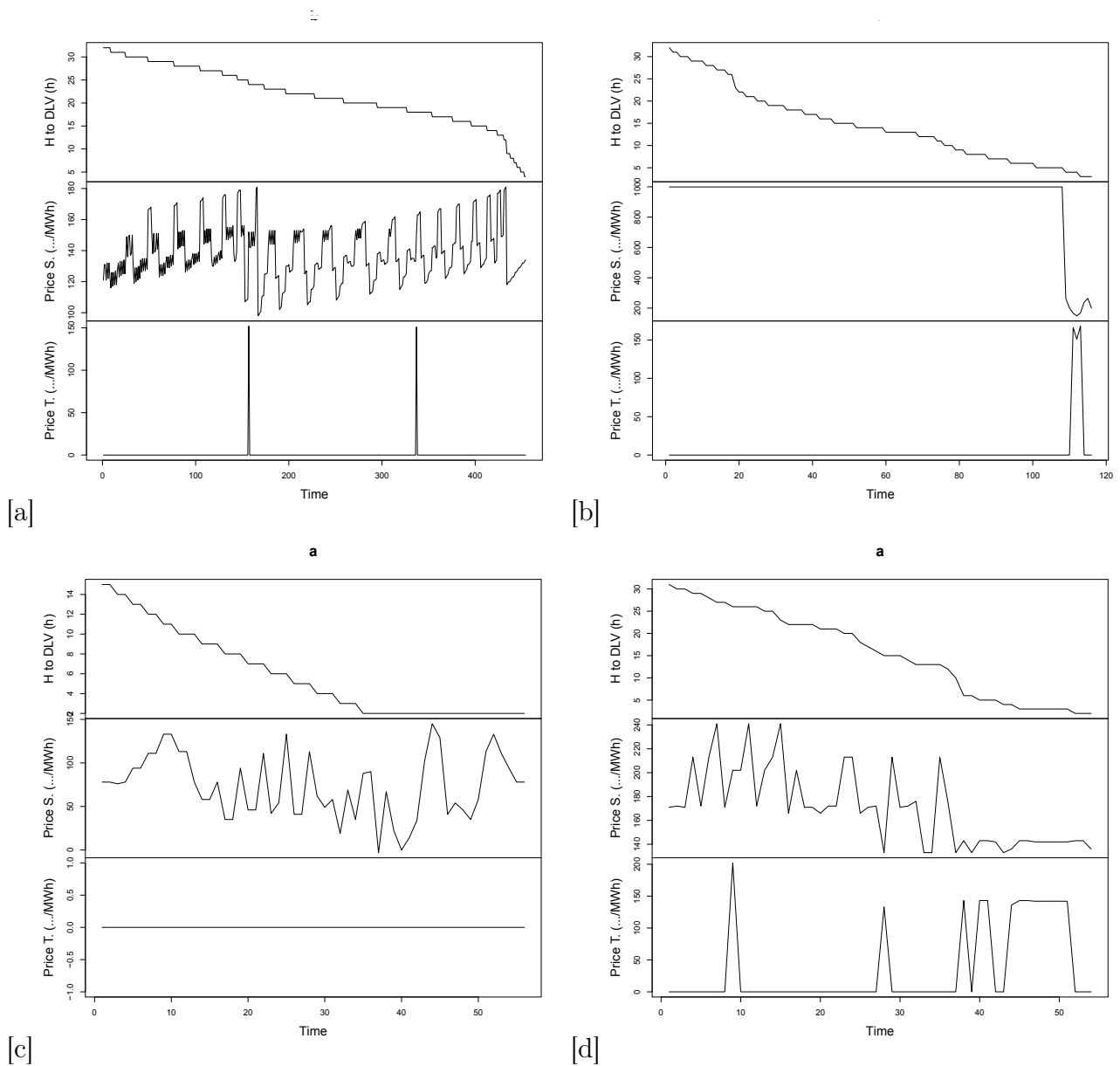


Figure 4.15: Time series of price in relation to the distance between the submission and delivery time for a solar (a), wind (b), hydro (c) and thermo-electric (d) power plant

Plot a shows the bidding strategy employed by a solar power plant for purchasing energy. Initially, it submits low-priced bids and gradually raises the offered price as the delivery time

approaches. Upon finding a successful match, it repeats the same trend, starting with a low price and increasing the bid as the session nears its end. Plot b illustrates the strategy employed by a wind power plant for selling energy. It attempts to sell at the maximum price throughout the session, and only three hours before delivery, it significantly reduces the price to secure a match. Plot c pertains to a hydro power plant that aims to purchase energy only during the final 14 hours of the session. During the first 11 hours, it submits bids at varying prices, while during the last three hours, it increases the price to improve the chances of finding a match. However, this strategy is ineffective as it fails to purchase energy throughout the entire session. Finally, plot d presents the strategy employed by a thermo-electric power plant for selling energy. Throughout the session, it submits offers at prices slightly higher than the market price, but it finds matches only with the lowest prices. During the final five hours, it reduces the energy prices, facilitating a successful match.

4.8.4 Price forecast

In this analysis, a regression function was developed to forecast the price trend for the four different power plants. Figure 4.16 presents the relationship between the orders price and the distance to the delivery time, overlaid with the regression line.

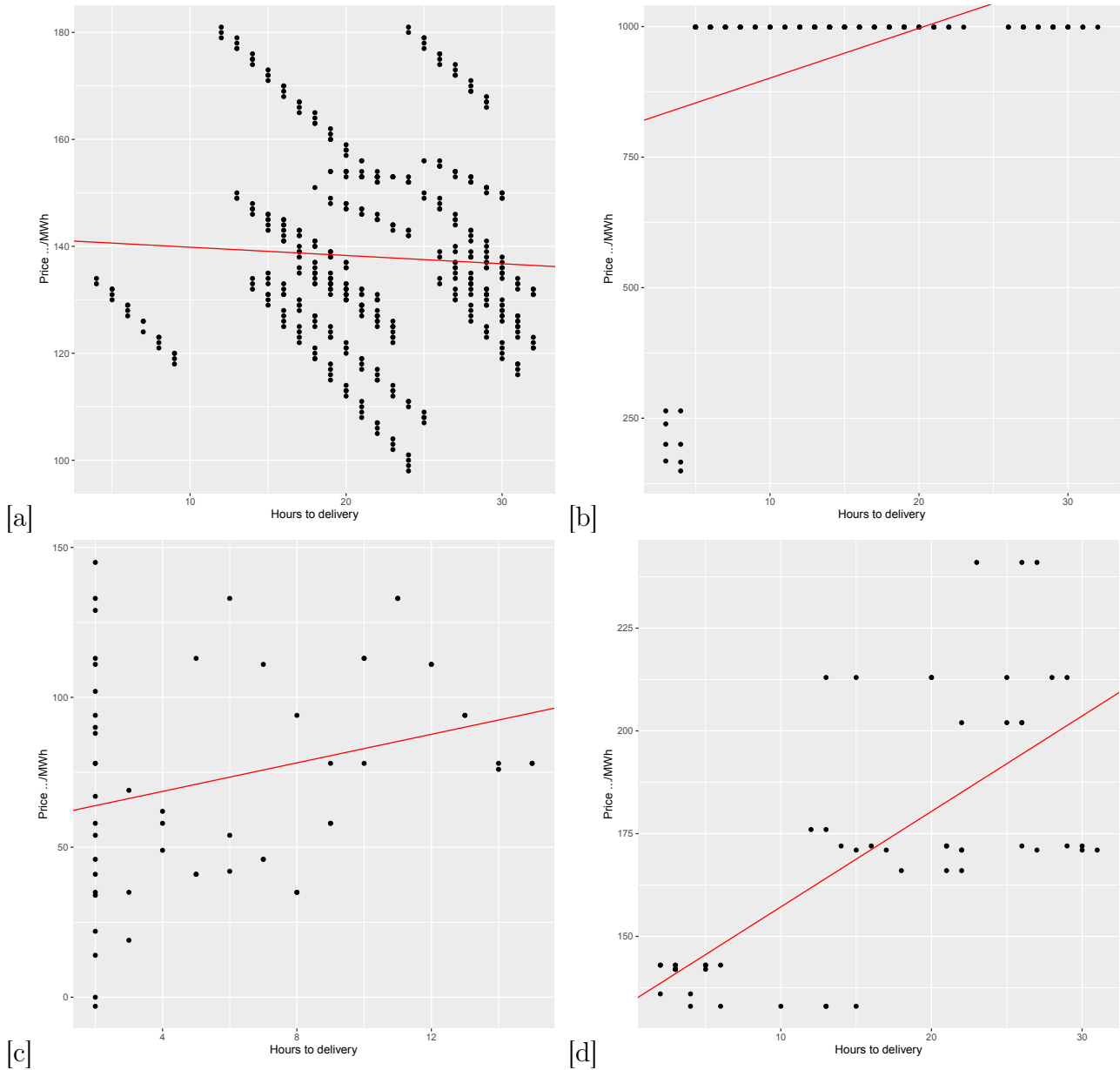


Figure 4.16: Regression of price in relation to the distance between the submission and delivery time for a solar (a), wind (b), hydro (c) and thermo-electric (d) power plant

The price trend analysis reveals that power plants' bidding strategies vary according to their type and objectives. The regression function shows that wind (b) and thermo (d) power plants, which aim to sell energy, decrease their prices as the delivery time approaches. Conversely, the solar power plant (a) increases its bid price as it aims to buy energy. However, the regression line for the hydro power plant (c) is counter-intuitive. Although it needs to buy energy and fails to find any match, the bid price trend strongly decreases, influenced by the large number of orders submitted during the last two hours of the session.

4.8.5 Relations between submissions and acceptance in terms of number of orders and prices

This subsection presents the correlation between the number of submitted and accepted orders and their corresponding submission and acceptance prices. Figure 4.17 displays the number of orders submitted and accepted as well as the average prices in relation to the temporal distance between the submission hour and the delivery hour.

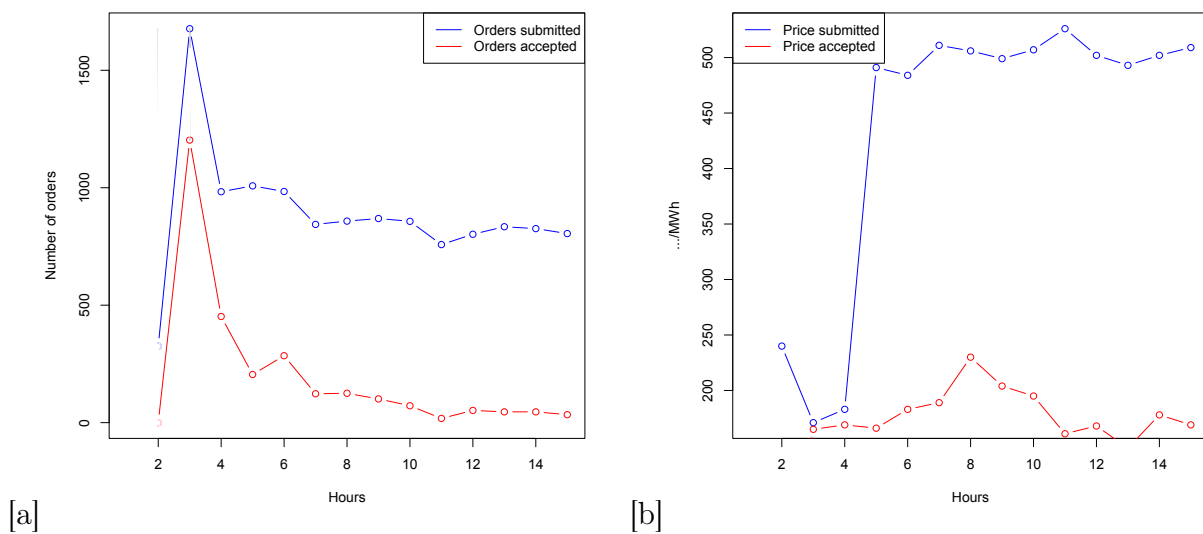


Figure 4.17: Number of orders submitted and accepted (a) and Price of orders submitted and accepted (b) in relation to the delivery time distance

The observed plot shape in figure 4.17.a reveals that the temporal behavior of the number of orders submitted and accepted is congruous, where both increase as the delivery time approaches, culminating in a peak three hours prior to delivery. The large gap between the two curves in earlier time periods indicates that agents initially submit few orders at prices substantially different from the market price, but increase submission frequency as the market approaches closing, leading to a significant rise in the number of matches. This phenomenon occurs because, as the delivery time approaches, submission prices tend to track the market price determined by the day-ahead auction, as demonstrated in figure 4.17.b. This plot reveals that submission prices are significantly higher than the accepted prices far from the delivery time, and the gap is narrowed only 4 and 3 hours before the energy delivery. It is also important to take into account the standard deviation of submission prices, which plays a crucial role in

determining price volatility, as shown in figure 4.18.

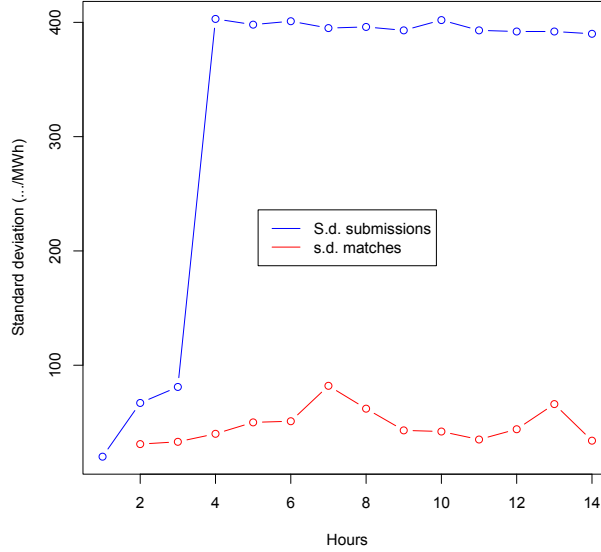


Figure 4.18: Standard deviation of submission and match prices

The standard deviation trends exhibit similarities to the price trends. Specifically, for submission prices, the standard deviation is found to be high far from the delivery time and it exhibits a sharp decline during the last four hours. This suggests that price volatility remains high during a substantial portion of the market session and agents resort to various strategies to purchase or sell energy. However, during the final hours of trading, the order prices converge towards the market price value.

4.8.6 Strategy for selling energy in continuous

We shall now introduce two novel parameters that can be inter-correlated to identify an effective strategy for energy bidding in continuous trading. The first parameter is the acceptance rate, which is characterized as the ratio of orders that obtain a match over the aggregate number of submissions:

$$AR = \frac{O_{acc}}{O_{sub}} * 100 \quad (4.6)$$

Here, O_{acc} refers to the number of orders accepted and O_{sub} refers to the number of orders submitted. The next parameter is the revenue expectation, which can be correlated with the previous parameter to determine a good strategy for bidding energy in continuous trading. This

parameter is calculated as the percentage between the average price of orders submitted and the margin between the submission and acceptance price.

$$RE = \frac{\mu_{P_s}}{\mu_{P_s} - \mu_{P_a}} * 100 \quad (4.7)$$

Where μ_{P_s} and μ_{P_a} represents the mean values of the price of orders submitted and accepted respectively.

The submission-acceptance margin price is the numerical difference between the price of the order submitted and the price at which the order finds a match. For example, if a seller submits an offer of 50€/MWh, it can obtain a match only with buy orders at the same or higher price. If it obtains a match with a 50€/MWh bid, its margin is zero.

In figure 4.19 the trend of the acceptance rate (AR) of the submissions and the revenues expectations (RE) is built in relations to the distance to the delivery time.

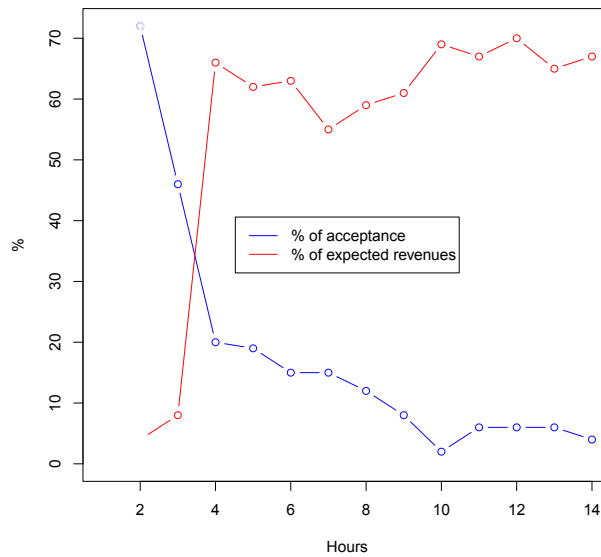


Figure 4.19: Acceptance rate and expected revenues in relations to the delivery time distance

The acceptance rate tends to increase as the delivery time approaches, which can be attributed to two factors discussed in the previous analyses: the rise in orders and the convergence of prices towards the market price. Conversely, the expected revenues tend to decrease towards the end of the market session as sellers lower their order prices to increase the likelihood of obtaining a match and avoid ending the session with an unbalanced portfolio. The point of

intersection between the two curves provides the optimal time-frame during which agents have a high probability of finding good revenue matches. Prior to this point (i.e., the right part of plot 4.19), finding a match is challenging due to low order volumes and significant price volatility, but it is also the time-frame during which agents can find the most profitable matches. After this point (i.e., the left part of the plot), the market becomes very liquid due to the large number of orders, and agents can easily find matches without having high revenue expectations.

4.9 Considerations

In conclusion, this section provides a comprehensive analysis of the behavior exhibited by different market operators through various statistical techniques. The probability density function analysis reveals that agents predominantly engage in significant energy exchange through continuous trading during the last 3/4 hours leading up to the delivery time. The number of orders submitted increases significantly as the delivery time approaches. Moreover, there is a noticeable decrease in the gap between the number of orders submitted and accepted during the final 3/4 hours before delivery. This can be attributed to agents submitting orders with higher prices in an attempt to maximize their revenues, despite the reduced likelihood of finding a match. Conversely, close to the delivery time, agents strive to balance their positions, leading them to submit orders around the market price and thereby increasing the probability of energy exchange. Furthermore, the time-series analyses highlight the adoption of different price trend strategies by agents. Non-dispatchable power plants exhibit a constant increase (or decrease for buyers) in order prices as the delivery time approaches, or they attempt to maximize revenues by submitting orders at the maximum allowable price until the final hours when they converge to the market price. Dispatchable power plants, such as thermal and hydro, submit orders with prices slightly higher (or lower for buyers) than the market price throughout the session and align their prices with the market price only in the last hours. Notably, the market price is derived from the day-ahead market. Analyzing the price trend throughout the 24 hours of the day reveals that the submission prices in continuous trading follow the prices determined in the dam auction. Specifically, the median of prices exhibits a strong correlation with the dam prices, whereas the mean is not always an accurate measure for studying price trends due

to instances where agents submit a few orders with prices significantly higher or lower than the effective match prices. Considering these characteristics, a novel strategy is formulated that focuses on the probability of finding a match and the expected revenues. A specific time frame is identified in which agents can optimize their revenues while maintaining a favorable probability of finding a match. In summary, this research provides valuable insights into the behavior of market operators in the European intraday market, particularly in the context of continuous trading. The statistical analyses conducted shed light on the patterns of order submission, price trends, and the influence of the day-ahead market on the intraday market. The findings contribute to a deeper understanding of the dynamics and strategies employed by market participants, ultimately supporting the development of more effective and efficient trading approaches.

Chapter 5

Energy continuous trading market models

This chapter aims at analyzing the possible economic and financial modelling techniques applicable to continuous trading electricity markets, with the objective to build a model capable of replicating the results as much precisely as possible. An overview of the economic models able to describe the continuous trading markets is presented. In particular, optimization, equilibrium and simulative models are discussed, focusing on the different game theory techniques that describe the strategies that can be implemented by market players to optimize their profits or to reach an equilibrium in a cooperative way. A further in-depth analysis is carried out on the simulative models, that are considered the best ones to be applied to the intra-day continuous trading electricity markets [75]. Then, a description is reported of the algorithms most used in the literature to simulate the strategies of the market players aimed at maximizing their profits, on the basis of information coming from the market itself, from external events or from the historical data available to each player [4]. A specific focus is carried out on the adaptive-aggressiveness model by Vytellingum [19], that can describe the willingness of an agent to be active in the market on the basis of the information that he/she receives during the trading session. Finally, two innovative models for the simulation of the continuous trading electricity market are presented. The first one, starting from the adaptive-aggressiveness model, optimizes the strategies of the market players using a genetic algorithm that iteratively modifies the main parameter of the model by Vytellingum, optimizing the social welfare and the exchanged energy. The second, instead, is a model able to replicate the peculiar aspects of the continuous trading market, such as its efficiency, the trend of the prices depending on factors internal and

external to the market and the frequency of order submission by the players. The two models are then applied to some test cases and the results are presented.

5.1 Game Theory Strategies Adoptable by Participants in Energy Markets

In the literature, several models can be found that are capable of studying and replicating the outcomes of a continuous trading market. In order to evaluate which model might be most suitable for the objectives of the study presented here, it is appropriate to first present the advantages and disadvantages of general models that describe financial markets, particularly considering the interaction among participants. The mathematical discipline that deals with the study of strategic interaction among individuals participating in a market is called game theory. Its purpose is to analyze situations in which different players interact while pursuing common, different, or conflicting objectives [76].

The approaches analyzed for modeling the continuous trading market of energy using game theory have been divided into two main categories: equilibrium models and simulation models. The present study focuses on simulation models as they are considered more suitable for the purpose. However, both models will be described below.

Equilibrium models are one of the most commonly used approaches in literature [77] [78] to study the possible interactions between agents participating in the electricity market through auction or continuous trading. These models are capable of simulating market prices and the profit of each individual player by replicating the different strategies and interactions with other agents. The variables considered include the price and quantity offered by each agent in order to maximize their own profit. The different strategies of the agents, network constraints, and the use of various computational methods have led to the formulation of multiple variants of equilibrium models. Among these, the most important ones are:

- **Bertrand Model:** The agents seek to maximize their profits by competing on the best offering price and assuming an equal volume of supply for all agents involved, which collectively covers the entire demand. This model is mainly used to study duopolies.

The model assumes that the agent with the lowest energy production costs will satisfy the entire demand if possible. If there are no production limitations or transmission costs, the market price will eventually correspond to the marginal production costs. For more details on the formulation of this strategy, refer to [14]. However, the Bertrand model cannot fully represent electricity markets as in reality, each agent has the ability to add a mark-up to their production costs. Additionally, the quantity of energy for sale is limited by the agent's production capacity [79]. This aspect cannot be overlooked in a continuous trading market where players must formulate strategies considering the quantities of energy to be traded in order to remain balanced. Nonetheless, examples of electricity market models following the Bertrand approach can be found in the literature, such as in [80].

- Cournot Model: In order to maximize profit, each agent considers only the volumes of energy to be offered on the market as variables, regardless of the offers made by competitors, which are therefore considered fixed. The Cournot model is often applied in literature to electricity markets [81]. However, in a continuous trading market, it is not the most appropriate model as the quantity offered by each actor depends on the need for buying and selling in order to avoid possible imbalances.
- Stackelberg Model: One agent (the leader) holds a dominant position and has greater market power than other agents. The leader agent chooses the quantity of energy to sell first, considering the reactions of other agents, who then adjust to his choice. The results of a study conducted on the electricity market in Colorado [82] show how the dominant agent can strategically congest market zone interconnections by offering energy at higher prices than its competitors. This strategy could be useful for studying how an agent can dominate the continuous trading market at the expense of others, a topic not addressed in the present report.
- Supply Function Model: Agents compete in terms of both quantity and price without fixing either of the two variables beforehand. The solution is obtained by solving a set of differential equations, greatly complicating the resolution process and making the solution

not always unique or existing. With specific assumptions, the model can be simplified, as in [83], where this model is implemented in a system composed of a single market zone. In many studies, the supply function is implemented with a time-independent linear demand function and marginal costs are also described by linear functions. A significant complication is indeed given by the fact that the marginal costs of each agent differ from each other, thus increasing the number of differential equations to be solved, as in [84], where simplification is obtained by equating the production capacity limits of different agents. As a result, this method is often used only to study small and relatively simple market scenarios, thus deviating from the main objective of this work.

- **Conjectural Variation Model:** In maximizing their own profit, an agent estimates how rival agents will define their outputs (volumes of energy to be offered on the market) in response to their own choices [85]. The parameter called 'conjectural variation (CV)' represents the estimate of the rivals' reaction. In [86], an iterative method is proposed to estimate the CV parameter based on historical data and statistical time series models that predict the evolution of the parameter over time. In general, the main problem of this strategy is precisely the estimation of the CV parameter. Regarding the representation of a continuous trading market, we believe that this model still presents the same issues as the Cournot strategy: each agent does not treat different quantities of energy depending on what rivals do, but is always guided by the avoidance of possible imbalances. This method could be used if only programmable generation plants that are not subject to any failure were to act in the intra-day market.
- **Conjectural Supply Function Model (CSF):** Agents estimate how rivals will react to their own price changes. The CSF differs from the 'supply function' in that the former is based on the assumption of a parameter that describes how the agent estimates rivals' reactions to their own changes in the bidding strategy, while in the latter, this parameter is endogenous in the model and depends on rivals' supply function. There are few studies that use the CSF model to simulate the electricity market: one of these is [87], which compares the CSF method with classical game theory methods. From the perspective of the continuous trading electricity market, as mentioned several times before, an agent

must formulate bids not only based on offers made by rivals but must also take into account external events that may lead to the risk of imbalances and a consequent decrease in revenues. For this reason, the CSF strategy is not considered completely suitable for representing a continuous trading market model.

An alternative to equilibrium models, especially in complex problems, is represented by **simulation models**, where the decisions and strategies of agents are well-defined variables within the model itself [88]. It is mainly used in stochastic processes where the system is simulated using probability distributions. The classic simulation models for the electricity market are agent-based models. In these models, agents are considered "intelligent" individuals capable of receiving information from the market and the external environment and then adapting and evolving their behavior in order to maximize certain objectives. Each agent must [89]:

- be identified by particular characteristics (such as the technology used to produce energy);
- maintain a well-defined behavior (maximize profits, minimize costs, maintain balance over time);
- be able to adapt and modify its behavior in response to variations due to external events or in reaction to the behavior of other agents.

Through an agent-based model, it is possible to identify the general characteristics of the system starting from the characteristics of individual agents. A typical agent-based model must have three fundamental elements [90]:

- a set of agents with specific characteristics;
- a set of rules that define what types of interactions can occur between agents;
- the environment in which agents interact.

In energy markets, agents use the available information, even if partial or incomplete, and combine it with their past experiences and the constraints of the system in order to formulate the best strategies to achieve their objectives. Agent-based models allow for the description of the interaction between the physical constraints of the electricity market and the behavior of

agents, and therefore allow for the analysis of the effects that different strategies have on the entire system. For this reason, these models are the most suitable for pursuing the objective of the study reported in this report.

In summary, equilibrium models are able to explain the interaction that occurs between different agents who rationally aim to maximize their profits, and therefore are often used to simulate electricity markets. However, when representing complex scenarios that consider multiple variables such as price formulation, generation constraints, interactions between agents, and interactions with the environment in which they operate, these models are complex to implement and require particular assumptions that may affect their results.

On the other hand, agent-based simulation models are able to reproduce all the characteristics of agents, their interactions, and interactions with the external environment. They require a rigorous and precise initialization, where the characteristics of each individual agent and the external environment are defined, but they provide comprehensive results regarding both the outputs of each player and the general characteristics assumed by the market scenario. Therefore, they are the most suitable for representing the continuous trading electricity market.

The second part of this chapter provides a detailed description of these models and how they have been used to simulate energy markets.

In the field of modeling electricity markets, the most commonly used agent-based models are Continuous Double Auction (CDA) models [91].

The trading mechanism that takes place in the market defines the exchanges between buyers and sellers based on their decisions (whether and when to submit an offer) and based on the consequences of their choices (whether a transaction occurs and at what price). In the CDA model, a fixed trading period is established in which agents can submit purchase or sale offers at any time, and the results are communicated whenever a transaction occurs (i.e., a match between supply and demand). The decisions made by the agents are public and accessible to all other agents participating in the market.

These models are used to study different types of markets, not just the electricity market, as reported in [92]:

"Markets organized under double-auction trading rules appear to generate competitive out-

comes more quickly and reliably than markets organized under any alternative set of trading rules."

Before going into detail about the different possible strategies adopted in agent-based models, it is useful to categorize them into four main groups based on the behavior of agents regarding historical data of the market and whether they are influenced by external information:

- Absence of historical data: These strategies, based solely on current market information and instantaneous variations, make decisions without considering previous transactions.
- Presence of historical data: These strategies are more complex than the previous ones because, based on the current conditions observed in the market, they also act based on information obtained from past events. They can be further divided into:
 - Non-predictive strategies: hypotheses are formulated based on historical data, and the most suitable one is chosen at that moment.
 - Predictive strategies: a forecast, as accurate as possible, of the market trend is made, and action is taken
- Absence of external information Agents implement strategies solely based on the information they gather from the market itself, such as changes in prices and volumes of offers or the quantity of offers submitted in certain periods of time.
- Presence of external information Agents take into account external information that does not strictly depend on the market, such as weather changes that can affect the production of renewable energy plants or possible malfunctions in plants that indirectly impact market prices and volumes.

The following section describes the most commonly used strategies in literature to replicate the behavior of actors in the continuous trading electricity market through agent-based models. Each strategy is evaluated based on efficiency, which refers to the tendency of the market to achieve an equilibrium price that satisfies both demand and supply and maximizes the general welfare of the system.

- **The Kaplan strategy** [93] is developed without the use of historical data and in the absence of external information. It does not aim for a general market equilibrium, but each agent aims to maximize its own profits. By analyzing the offers of other competitors, an agent formulates offers when one of the following conditions occurs: - The best selling offer (defined as the offer presented at the lowest price) has a lower price than the lowest price among all previous transactions. - The best selling offer has a lower price than the highest price among all previous transactions, and the quotient of the price spread between supply and demand and the best selling offer is lower than a factor called the "spread factor," while the expected profits are higher than a factor called the "profit factor." - The remaining time fraction for a potential offer is less than a "time factor." The three mentioned factors must be defined in advance in the model. This strategy is only successful if implemented by a single market participant, as if all agents were to adopt it, no one would offer while waiting for one of the aforementioned conditions to occur.
- **The zero-intelligence (ZI)** strategy by Gode and Sunder [94] is developed without historical data and external information. Agents formulate their offers without considering market conditions and without aiming to maximize their profits, but rather present orders at random prices defined by a normal distribution around a certain price level. The results of this model, reported in [94], show that the offers made by agents have a slight convergence towards a specific price, just like in the real continuous trading market. The results of the analyses conducted by Gode and Sunder demonstrate that the market is efficient even if agents do not have true strategies to maximize their profits. However, there are agent-based models that attribute different strategic pricing logics to agents, which achieve significantly higher efficiencies in terms of maximizing welfare and minimizing imbalances.
- **The zero-intelligence plus (ZIP)** strategy was formulated by Cliff and Burten in [95]. Unlike the ZI strategy, it considers both historical and current market information, and agents aim to increase their profits. At the market opening, each agent has an arbitrary profit margin that can increase or decrease over time depending on events. For example, a

buyer increases their profit margin when they see that they can buy energy at a lower price than the price they set to obtain initial profits. The results of applying this technique show that the transaction price converges towards an equilibrium price, which tends to remain stable until the end of the session. Although this model yields excellent results regarding market price trends under certain conditions, it does not take into account external factors that we believe are fundamental for the real modeling of the intraday energy market.

- **The strategy by Gjierstad and Dickhaut (GD)**, reported in [96], uses historical market data but does not make predictions about its future behavior. It is based on a function that each agent constructs to understand whether a particular offer will be accepted in the market. This function is based on expectations that agents define based on the frequency of offers presented and accepted. The number of past offers presented and accepted must be chosen in advance. The results of using this strategy show that the market efficiency is very high, as all operators manage to minimize imbalances, and prices converge rapidly to the competitive equilibrium price of the market. Compared to the previously described techniques (ZI, ZIP, and Kaplan), the GD strategy was found to be the most efficient. However, once again, this strategy does not take into account possible weather variations or potential generation plant malfunctions, which are the factors that most influence the strategies adopted in reality by market participants.
- Tesauro and Bredin [97] were able to implement a more refined strategy than the GD strategy called **GDX**. They introduce a time factor into the algorithm, allowing the agent to wait to present an offer when market conditions are most favorable. The results of this strategy are highly efficient, minimizing imbalances and increasing profits as much as possible. However, in some cases, they do not surpass the efficiency of the GD strategy. Just like GD, fundamental external factors for simulating the continuous trading electricity market are not taken into account.
- The last strategy analyzed, the **adaptive-aggressiveness strategy** [19], introduces a new concept called aggressiveness. Aggressiveness refers to an agent's inclination to in-

teract more or less actively in the market. An aggressive agent presents offers at a better price (lower if selling and higher if buying) than what they believe to be the competitive equilibrium price, thereby increasing the chances of obtaining a match at the expense of profit. On the other hand, a passive agent presents offers at a "worse" price than the equilibrium price, reducing the chances of obtaining a match but achieving a higher profit margin. The aggressiveness range, denoted as r , varies in the interval $[-1, +1]$: a passive agent has $r < 0$, while an aggressive agent has $r > 0$. For $r = 0$, the agent presents offers at the same price as the competitive equilibrium.

The adaptive-aggressiveness strategy is based on the agent's predictions and expectations in both the short and long term to adjust its behavior over time. Short-term expectations modify the agent's aggressiveness based on market information regarding the presented offers. Long-term expectations determine how the aggressiveness factor influences the offers that the agent wants to present in the market.

This strategy proves to be one of the best for simulating the continuous intraday market and, for this reason, a mathematical description of this strategy is provided below. Let \hat{p}^* be the market price calculated by each individual agent:

$$\hat{p}^* = \sum_{i=T-N}^N \left(\frac{w_i \cdot p_i}{N} \right) \quad (5.1)$$

where T represents the last transaction made, N represents the number of recent transactions considered for the calculation, w_i and p_i denote the weight given to each transaction and the price at which the transaction occurred, respectively. Agents are then divided into two macro-categories: intra-marginal and extra-marginal.

A buyer (seller) is intra-marginal if their price limit is higher (lower) than the equilibrium price. On the other hand, a buyer (seller) is extra-marginal if their price limit is lower (higher) than the equilibrium price.

Therefore, each agent is defined based on three characteristics: 1. Buyer or seller. 2. Intra-marginal or extra-marginal. 3. Passive or aggressive.

Thus, it is possible to define eight different price formulation strategies. Let l_i be the

highest offer price that buyer i can present, c_j be the lowest offer price that seller j can present, MAX be the highest acceptable price in the market, and θ be a parameter depending on long-term learning. The following offer prices can be derived:

Intra-marginal passive buyer:

$$p = \hat{p}^* \left(1 - \frac{e^{-r\theta} - 1}{e^\theta - 1} \right) \quad (5.2)$$

Intra-marginal aggressive buyer:

$$p = \hat{p}^* + (l_i - \hat{p}^*) \left(\frac{e^{r\theta} - 1}{e^\theta - 1} \right) \quad (5.3)$$

Intra-marginal passive seller:

$$p = \hat{p}^* + (\text{MAX} - \hat{p}^*) \left(\frac{e^{-r\theta} - 1}{e^\theta - 1} \right) \quad (5.4)$$

Intra-marginal aggressive seller:

$$p = c_i + (\hat{p}^* - c_j) \left(1 - \frac{e^{r\theta} - 1}{e^\theta - 1} \right) \quad (5.5)$$

Extra-marginal passive buyer:

$$p = l_i \left(1 - \frac{e^{-r\theta} - 1}{e^\theta - 1} \right) \quad (5.6)$$

Extra-marginal active buyer:

$$p = l_i \quad (5.7)$$

Extra-marginal passive seller:

$$p = c_j + (\text{MAX} - c_j) \left(\frac{e^{-r\theta} - 1}{e^\theta - 1} \right) \quad (5.8)$$

Extra-marginal active seller:

$$p = c_j \quad (5.9)$$

Through what is called a short-term process, each agent adapts their aggressiveness based on the market trends as follows:

$$r(t+1) = r(t) + \beta_1(\delta(t) - r(t)) \quad (5.10)$$

where

$$\delta(t) = (1 \pm \lambda_r)r_{\text{shout}} \pm \lambda_a$$

Where $\delta(t)$ is the desired aggressiveness that would allow a buyer (seller) to buy (sell) energy at the lowest (highest) possible price, r_{shout} is the level of aggressiveness that would allow a buyer (seller) to present an offer with a price equal to the last matched purchase (sale) in the market, $\beta_1 \in (0, 1)$ is the degree of aggressiveness adaptation, and λ_r and λ_a are the relative and absolute increments or decrements of r_{shout} .

On the other hand, the long-term process influences the parameter θ , which is dependent on price volatility:

$$\theta(t+1) = \theta(t) + \beta_2(\theta^*(\alpha) - \theta(t)) \quad (5.12)$$

$$\alpha = \sqrt{\frac{1}{N} \sum_{i=T-N+1}^T \left(\frac{p_i - \hat{p}_i^*}{\hat{p}^*} \right)^2} \quad (5.13)$$

$$\theta^*(\alpha) = (\theta_{\max} - \theta_{\min}) (1 - \theta e^{\gamma(\alpha-1)}) + \theta_{\min} \quad (5.14)$$

where θ_{\min} and θ_{\max} represent the range within which θ can be calculated, and γ determines the shape of the function.

Once a price is formulated, it is not necessary for the agent to submit an offer. In fact, if a buyer (seller) has a price limit lower (higher) than the orders in the order book (i.e., the

platform where unmatched orders are stored - its functionalities will be explained further in the next Section), they will not submit any offer and wait for more favorable market conditions.

This strategy has been shown to be the best among those analyzed. Several studies [38] have demonstrated its significantly higher efficiency compared to the other strategies mentioned earlier.

In this second part of the chapter, several possible strategies based on the agent-based model capable of simulating continuous double auction energy markets have been presented. Each of these approaches implements specific strategies that lead the market to converge to an equilibrium point that satisfies the demand and supply of the participating agents. The six types of strategies presented are the most commonly used to simulate a continuous auction market, as they all exhibit excellent levels of efficiency. However, to date, the adaptive aggressiveness strategy formulated by Vytellingum is considered to best simulate the market, achieving efficiency levels close to 100%. Although even this strategy does not consider external factors such as weather variables, we consider it to be the best strategy implemented to date.

It is based on this strategy that two models have been developed to simulate continuous auction energy markets, also replicating their most characteristic aspects.

Chapter 6

FORMULATION OF CONTINUOUS AUCTION MARKET MODELS

In order to accurately replicate the continuous auction electricity market, two innovative models have been implemented using MATLAB. The first model describes a test scenario of energy trading where the agents' strategy is characterized by their level of aggressiveness, similar to the adaptive-aggressiveness (A.A.) strategy described in the previous chapter. In contrast to Vytellingum's strategy, genetic algorithms are used to assign each agent the best strategy that maximizes welfare and minimizes imbalances. The second model replicates the common aspects of the continuous auction market, as described in the statistical analyses in [23] [25] [24], by dividing the agents into those offering energy produced from thermal power plants and those with renewable energy sources. Each plant is characterized by specific strategies that are closely dependent on both internal and external market conditions, such as failures, price fluctuations, and variations in weather conditions. Both models share the common feature of accurately replicating the operation of the 'shared order book,' which is a characteristic of the SIDC platform.

6.1 Order book

In this section, simulations of continuous trading and the subsequent management of a centralized order book are described, conducted using a specially developed simulation tool. This

tool, which assumes for simplicity that the order book pertains to a single Market Time Unit (e.g., for hourly products), enables various experimentation activities that, when combined with analysis, enhance the understanding and study of the dynamics inherent in continuous trading and the behaviors of market operators who adapt their bidding strategies based on continuous price signals received from the market.

6.1.1 Order book simulation

The simulation tool used consists of the "dex" application, implemented in the Go programming language, with a client-server architecture. It is divided into two components: "dexd" is the server component, which listens for commands and manages the order book, while "dexc" is the client component, which simulates the submission of orders by multiple buyers and sellers. The server part is activated through the command line, with two optional parameters:

```
dexd [-lastprice #] [-httpport #]
```

where:

- "lastprice" indicates the initial value of the market price to use in case of server interruption and subsequent reactivation. Normally, it is set to the last valid market price at the time of server interruption. If not specified, the value is assumed to be 0.0.
- "httpport" indicates the value of the HTTP port on which the server should listen. If not specified, the value is assumed to be 9771.

Commands can be sent to the server from any browser, such as Chrome, or from applications capable of handling the HTTP protocol, such as "curl," or from the dedicated client "dexc," which allows for the bulk submission of orders constructed according to specific bidding strategies. The possible commands to activate specific server functionalities are as follows:

- "start": restarts the already running server.
- "stop": generates files with information regarding the submitted orders and executed matches.

- "submit": submits an order.
- "inquiry book": queries the status of the order book.
- "delete order": removes an order from the order book.
- "inquiry order": queries the status of an order.

This set of commands is sufficient to implement the desired bidding strategy in the client.

In the following descriptions, the TCP address 192.168.1.103 is shown as assigned to the machine running the server during the tests. It should be replaced accordingly if the server is running on a machine with a different TCP address. To send HTTP requests to the server, the "curl" utility has been used in the examples. The "-s" parameter suppresses its data transfer-related traces, and the JSON responses are displayed in structured form by the "jq" program.

6.1.2 Functionality of the Server

start

This command restarts the already running server, forcing the clearing of the order book, resetting the identifiers associated with orders and matches, and resetting the log traces. It is useful to bring the server back to a known initial condition, erasing all previous data. There is no return information.

Example:

```
curl -s "http://192.168.1.103:9771/start"
```

submit

This command allows the submission of "limit orders," specifying the price and quantity, as well as "market orders," only indicating the quantity, both for buying and selling. The following optional restrictions can also be specified:

- "fok": indicates the "fill-or-kill" condition, where the order is only satisfied if a counterparty for the entire quantity is found in the order book; otherwise, it is ignored.
- "ioc": indicates the "immediate-or-cancel" condition, where the order is only satisfied if a counterparty, even for a partial quantity, is found in the order book; otherwise, it is ignored.

Orders with "fok" and "ioc" restrictions are never inserted into the order book.

Example of submitting a sell "limit order" without restrictions, with a price of 100 and a quantity of 50, and the corresponding JSON response from the server:

```
curl -s "http://192.168.1.103:9771/submit?action=sellprice=100quantity=50" | jq
```

```
{
  "OK": true,
  "ID": 1,
  "Action": "sell",
  "Limit": true,
  "Price": 100,
  "Quantity": 50,
  "ResidualQuantity": 50,
  "Matches": null,
  "Deleted": false,
  "FOK": false,
  "IOC": false
}
```

The "OK" field indicates whether the order was successfully received by the server or not. The "ID" field shows the numerical identifier assigned by the server to the order within the

order book. The "Action," "Price," and "Quantity" fields replicate the information provided by the operator with the order and received by the server. The "Matches" field, set to null, indicates that the received order has not been matched with any other order. The "Limit" field identifies the order as a "limit order," allowing its insertion into the order book in the absence of a match.

Example of submitting a buy "limit order" without restrictions, with a price of 110 and a quantity of 60, and the corresponding JSON response from the server:

```
curl -s "http://192.168.1.103:9771/submit?action=buyprice=110quantity=60" | jq
```

```
{
  "OK": true,
  "ID": 2,
  "Action": "buy",
  "Limit": true,
  "Price": 110,
  "Quantity": 60,
  "ResidualQuantity": 10,
  "Matches": [
    {
      "OrderSeq": 2,
      "BookOrderSeq": 1,
      "Price": 100,
      "Quantity": 50
    }
  ],
  "Deleted": false,
  "FOK": false,
  "IOC": false
}
```

This buy order has been matched with the previous sell order for a quantity of 50. The previous sell order is removed from the order book as it has been satisfied for its entire quantity. The buy order is inserted into the order book for its remaining quantity of 10. The status of the order book can be obtained using the "inquiry book" functionality.

inquiry book

Example of requesting the state of the buy order book:

```
curl -s "http://192.168.1.103:9771/inquiry/book?action=buy" | jq
```

```
{"OK": true,"LastPrice": 100,"Depth": 1,"FirstPrice": 110,"BookOrders": [{ "ID": 2, "Price": 110,
```

The value of LastPrice indicates the market price, which is the same as the price of the last order extracted from the order book. The value of FirstPrice indicates the price of the best order present in the book. If a buy order with a higher price than the best price is placed in this state, there will be a reordering of the orders in the book based on price.

```
curl -s "http://192.168.1.103:9771/inquiry/book?action=buy" | jq
```

```
{"OK": true,"LastPrice": 100,"Depth": 2,"FirstPrice": 115,"BookOrders": [{ "ID": 3, "Price": 115,
```

inquiry order

To query an order from the book, it is necessary to specify its numerical identifier. Here is an example:

```
curl -s "http://192.168.1.103:9771/inquiry/order?seq=1" | jq
```

```
{"OK": true,"ID": 1,"Action": "sell","Limit": true,"Price": 100,"Quantity": 50,"ResidualQuantity": 0,
```

delete order

To delete an order from the book, it is necessary to specify its numerical identifier. Here is an example:

```
curl -s "http://192.168.1.103:9771/delete/order?seq=2" | jq
```

```
{"OK": true,"ID": 2,"Action": "buy","Limit": true,"Price": 110,"Quantity": 60,"ResidualQuantity": 10}
```

stop

This command creates the following files:

- orders.csv
- matches.csv
- userid.matchedquantity.csv

The first file contains a list of all received orders, the second file contains a list of all executed matches, and the third file contains the total matched quantity for each agent. The contents of these files are available for subsequent statistical analysis, especially if hundreds or thousands of orders are submitted.

Example:

```
curl -s "http://192.168.1.103:9771/stop"
```

There is no return information.

6.1.3 Client functionalities

As described in the section dedicated to server functionalities, the server's management of order matches and their storage within an order book in the absence of matches allows the development of continuous trading market simulations.

Beyond the manual submission of individual orders, as described above, it is possible to implement in dedicated applications the creation and submission of hundreds or thousands of orders to the server by different operators, each acting according to their own characteristics. These characteristics may include the quantity of energy that can be offered (if a seller) or requested (if a buyer), or the minimum price at which to offer (if a seller) or the maximum price to request (if a buyer).

The developed client is a separate application that simulates the creation and submission of orders to the server by operators with different characteristics. Its functioning is divided into two phases:

1. Creation of "agents," representing individual operators or their production and/or consumption facilities.
2. Creation and submission of orders by each agent.

There are multiple possible strategies for order submission, and in the implementation of the client, one has been arbitrarily chosen for the sole purpose of simulating a possible continuous trading operation in electricity markets.

Creation of agents

The phase of creating "agents" is governed by several configuration parameters defined by the client user. The logic adopted is as follows: N agents are randomly created, divided into "buyers" with a probability of P and "sellers" with a probability of (1 - P). Each agent is then assigned the following:

- A "private value" PV_i indicating the economic value attributed to energy and used as the price in the orders submitted by the agent.
- A "quantity" Q_i of total energy to be divided into one or more orders.
- A maximum number of "slices" S_i into which to divide Q_i into distinct orders.

The value of the "private value" is assigned randomly through a normal distribution with standard deviation and mean defined by the configuration parameters "std" and "mean," which are common to all agents:

$$PV_i = f_normal(std, mean)$$

The value of "quantity" is assigned randomly through a uniform distribution between a minimum value, close to zero, and a maximum value defined by the parameter "qmax," which is common to all agents:

$$Q_i = f_uniform(qmax)$$

The value of "slice" is assigned randomly through a uniform distribution between 1 and a maximum value defined by the parameter "smax," which is common to all agents. It indicates the maximum number of orders that an agent can submit:

$$S_i = f_uniform(smax)$$

6.1.4 Order book operation

The part of the market platform concerning the submission, storage, and matching of offers is referred to as the order book. Orders are stored according to a price-time priority criterion (the primary order criterion is based on price, and in case of the same price, the offer that has been present in the book for a longer time takes precedence) [53], as shown in Figure 6.1. The matching process follows the first-come-first-served rule, as illustrated below.

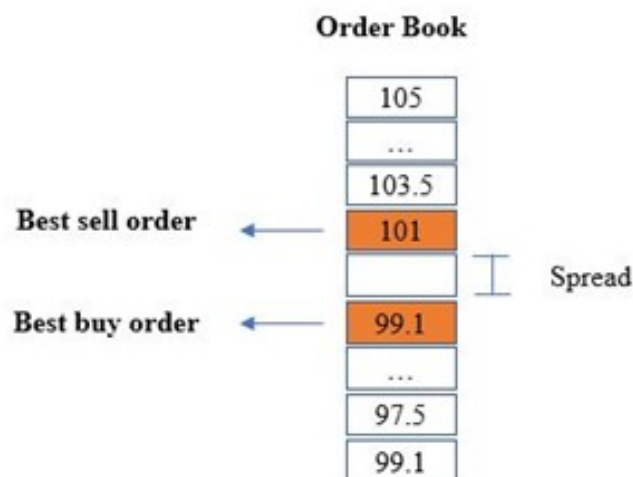


Figure 6.1: Order book representation

Orders can be fully matched, partially matched, canceled by the agent who submitted them,

or, as will be discussed later, canceled by the system. A sell (buy) order is fully matched if its price is lower (higher) than a buy (sell) order already present in the order book and if its volume is less than or equal to the volume of the offer with which it is matched. If there are multiple buy (sell) orders already present in the book, the order will be matched with the one having the highest (lowest) price. If two buy (sell) orders have the same price, the sell (buy) order will be matched with the one present in the book for a longer time. In the case where the offer has a larger volume than a matchable order already present in the book, it will be partially matched. That is, it will only be accepted for the part equal to the volume of the offer it is matched with; the remaining part will be left in the book with its price or will be matched with another order already present in the book, thus resulting in multiple matches. If the submitted order does not find any match, the agent can decide to cancel it by withdrawing it from the book. If the order does not find any match, and the agent chooses to leave it in the book, it will be removed from the system at the end of the trading session. Figure 6.2 shows a diagram of the possible functionalities of the order book.

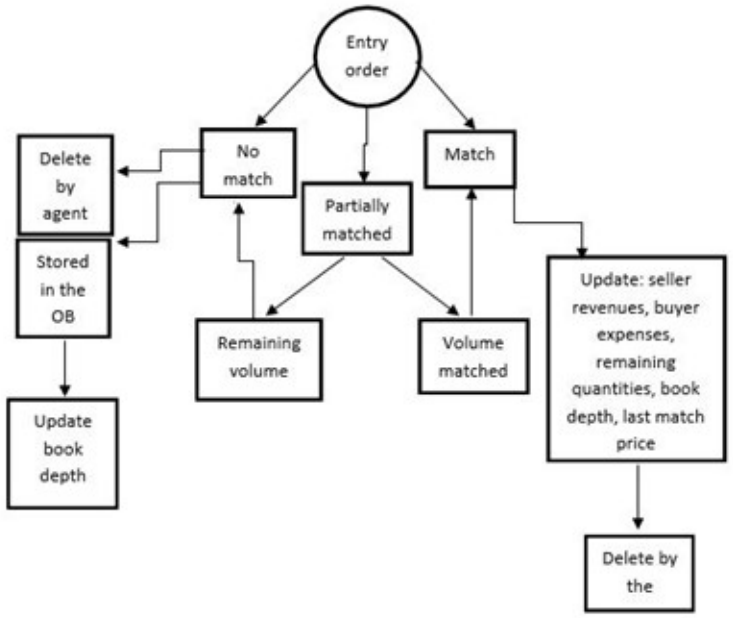


Figure 6.2: Order book operations

6.2 Genetics algorithm model

Genetic algorithms (GAs) are optimization techniques widely studied and applied in various engineering domains. In this study, they are used to find the best combination of strategies adopted by market agents to maximize overall welfare and minimize potential imbalances, as illustrated in 6.4. The agent-based model initially assigns strategies to the agents, which are then optimized by the genetic algorithm to satisfy the objective functions.

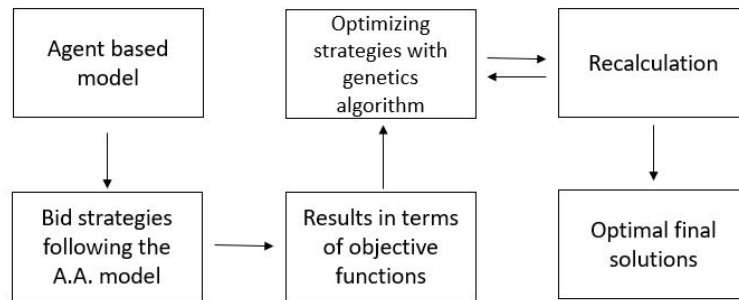


Figure 6.3: Agent-based model with genetics algorithm pattern

In general, genetic algorithms (GAs) find the best solutions to a problem and recombine them to evolve towards an optimal point. The process consists of the following five phases:

1. **Initialization:** The process starts with a set of individuals (initial population), each possessing genes (characteristics) that together form a chromosome (solution to the problem).
2. **Fitness Function:** A fitness function is defined to evaluate how well an individual is suited to solve the problem and how deserving it is to survive in the environment. This function assigns a score to each individual, and their probability of reproducing and passing their characteristics to the next generations depends on this score. This leads to the selection phase, where individuals with higher scores pass their genes (characteristics) to the next generation.
3. **Crossover:** Each pair of selected individuals exchanges genes to create new offspring through a process known as crossover.
4. **Mutation:** During the crossover phase, there is also a chance for mutation, where some characteristics of the individuals are randomly changed by the algorithm.

5. **Termination:** The algorithm stops when the characteristics of the new individuals do not differ significantly (or differ minimally) from the characteristics of the individuals in the previous generation.

This process allows genetic algorithms to find optimal solutions by iteratively evolving the population towards better solutions through selection, crossover, and mutation operations.

6.2.1 Optimal solutions of the model: the Pareto front

Before delving into the details of how genetic algorithms are used for optimizing an electricity market model, it is essential to understand what is meant by the Pareto front. The Pareto front represents a set of optimal solutions and consists of all non-dominated points, meaning there is no other point that is better than them across all considered objectives in the optimization function [98]. A solution x^* is said to be dominated by a solution x if x is better (or equal) than solution x^* with respect to a given objective function. The set of solutions is considered optimal when the result of any objective function cannot be improved without deteriorating the results of at least one other objective function [99].

Assuming that P is the set of non-dominated solutions from the set representing all solutions S , and N_{obj} is the total number of objective functions, the Pareto front of the set S can be written as:

$$P = \left\{ f = \begin{bmatrix} f_1(x_1) \\ f_2(x_2) \\ f_3(x_3) \\ \vdots \\ f_{N_{\text{obj}}}(x) \end{bmatrix}, x \in S \right\}$$

And it can be represented as in Figure 6.4

The Pareto solutions are the different optimal solutions that we find by applying genetic algorithms to market models.

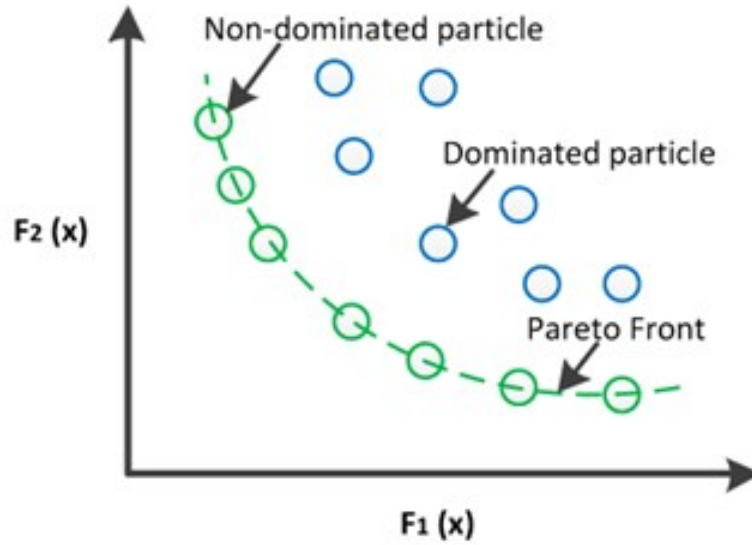


Figure 6.4: Set of a Pareto solutions

6.2.2 Genetic algorithm applied to an intraday energy market model

The chosen genetic algorithm for optimization is the Non-Dominated Sorting Genetic Algorithm (NSGA II) [100]. Through this algorithm, each individual in the population, representing market agents, is assigned a fitness score that describes their level of suitability in achieving specific objectives, as well as a crowding distance, which measures the isolation of the solution compared to others. For each solution from a Pareto front, the crowding distance is calculated; solutions aggregated in a cluster have a lower crowding distance compared to an isolated solution. Therefore, individuals are first sorted based on their assigned fitness and then, within the same Pareto front, based on the crowding distance. The fittest individuals are characterized by a low or high fitness value, depending on whether the objective function aims to minimize or maximize, and a high crowding distance. To generate a new population, the individuals with the best characteristics are combined through the crossover process and mutations, as explained earlier. The new individuals are then added to the initial population. Assuming there are initially N individuals, after the generation process, there will be $2N$ individuals [100]. The new generation is then sorted based on fitness and crowding distance, and the top N individuals are selected, while the others are discarded. The process continues until a predetermined maximum number of generations is reached or if the characteristics of the individuals in the new generation are the same as those of the previous generation. Each agent (individual in the

population) is characterized by their own aggressiveness value (gene), which determines their specific trading strategy in the market (environment). In each simulation, the effectiveness of the agents' characteristics is evaluated based on the results of the following four objective functions (where q_m^i , p_m^i , and p_o^i represent the matched quantity, matching price, and order submission price of agent i , while V_i^{\max} and V_i indicate the total volume of energy to sell/buy and the actual volume sold/bought by agent i).

- **Maximization of Sellers' Welfare** The sellers' welfare is defined as the profit margin relative to the offering price [101]. It aims to maximize the benefits of sellers participating in the market. The objective function for maximizing sellers' welfare is given by:

$$W_s = \sum_{i=1}^{N_{\text{sellors}}} q_m^i \cdot (p_m^i - p_o^i) \quad (6.1)$$

where W_s represents the total welfare of sellers, N_{sellors} is the number of sellers in the market, q_m^i is the matched quantity of seller i , p_m^i is the matching price, and p_o^i is the order submission price of seller i .

- **Maximization of Buyers' Welfare**

Similarly, the buyers' welfare is defined as the profit margin relative to the offering price. It aims to maximize the benefits of buyers participating in the market. The objective function for maximizing buyers' welfare is given by:

$$W_b = \sum_{i=1}^{N_{\text{buyers}}} q_m^i \cdot (p_o^i - p_m^i) \quad (6.2)$$

where W_b represents the total welfare of buyers, N_{buyers} is the number of buyers in the market, q_m^i is the matched quantity of buyer i , p_m^i is the matching price, and p_o^i is the order submission price of buyer i .

- **Maximization of Total Welfare**

The total welfare of the system is the sum of sellers' welfare and buyers' welfare. The objective function for maximizing the total welfare is given by:

$$W_{\text{tot}} = W_s + W_b \quad (6.3)$$

where W_{tot} represents the total welfare of the market.

- Minimization of Final Imbalance

The final imbalance at the end of the market session represents the difference between the maximum volume of energy intended to be sold/bought by each agent and the actual volume traded. The objective function for minimizing the final imbalance is given by:

$$V_r = \sum_{i=1}^{n_{\text{agents}}} V_i^{\text{max}} - V_i \quad (6.4)$$

where V_r represents the total final imbalance, n_{agents} is the total number of market agents, V_i^{max} is the maximum volume of energy to be sold/bought by agent i , and V_i is the actual volume of energy traded by agent i .

In the implemented model, multiple market sessions are considered, each with different assigned levels of aggressiveness to the agents. Since the NSGA-II algorithm allows for optimizing up to three objective functions, various combinations of the previously described objective functions have been implemented. This approach enables the evaluation of different sets of aggressiveness assigned to the agents to determine which yields the best results. To analyze the behavior of the algorithm, numerous simulations were conducted, some with two objective functions and others with three. By comparing and evaluating the results of these different simulations, it was possible to assess their performance, as detailed in the following section. Subsequently, the algorithm creates a new set of agents, each characterized by new levels of aggressiveness, and the effects on the objective functions are re-evaluated. This iterative process allows for the exploration of different strategies and the selection of the most optimal set of agent aggressiveness values.

6.2.3 Handling a Larger Number of Objectives

The current optimization framework has been intentionally structured to accommodate up to three objectives, striking a balance between computational efficiency and the complexity of the optimization task. However, recognizing the evolving landscape of research questions and the potential need for addressing a more extensive set of objectives, avenues for future enhancements are under consideration. Exploring alternative optimization algorithms beyond NSGA-II and adopting methodologies such as weight aggregation and Pareto dominance are potential strategies. These alternatives aim to extend the capability of the framework to handle a greater number of conflicting objectives. Weight Aggregation involves transforming conflicting objectives into a single aggregated objective by assigning weights to each objective. These weighted objectives are then combined into a scalar value, simplifying the optimization problem. It's essential to carefully select weights to reflect the relative importance of each objective. On the other hand, Pareto Dominance is based on the Pareto efficiency principle, where a solution is considered optimal if there is no other solution that is better in all objectives and at least as good in one objective. This method retains the multi-objective nature of the problem, identifying non-dominated solutions and forming a Pareto front. It is crucial, though, to judiciously assess these enhancements to ensure computational scalability and efficiency. Incorporating such refinements is anticipated to fortify the framework's versatility and its suitability for problem domains demanding the optimization of a larger set of objectives.

6.2.4 Results

In this section, we present some results from the two conducted simulations. The first simulation utilizes the adaptive-aggressiveness algorithm as formulated by Vytellingum, while the second simulation modifies the aggressiveness values through the genetic algorithm applied to the adaptive-aggressiveness approach. Specifically, we compare the final values of welfare and the quantity of unsold energy between the two simulations. Both simulations were performed under the same initial assumptions, including the number of players and initial strategies. In the first simulation, we observe the formation of the Pareto front (Figure 6.5) in a scenario consisting of eight agents (four buyers and four sellers). The objective is to minimize the expenditures of the

buyers and the unaccepted quantities to achieve a balanced market (minimizing imbalances).

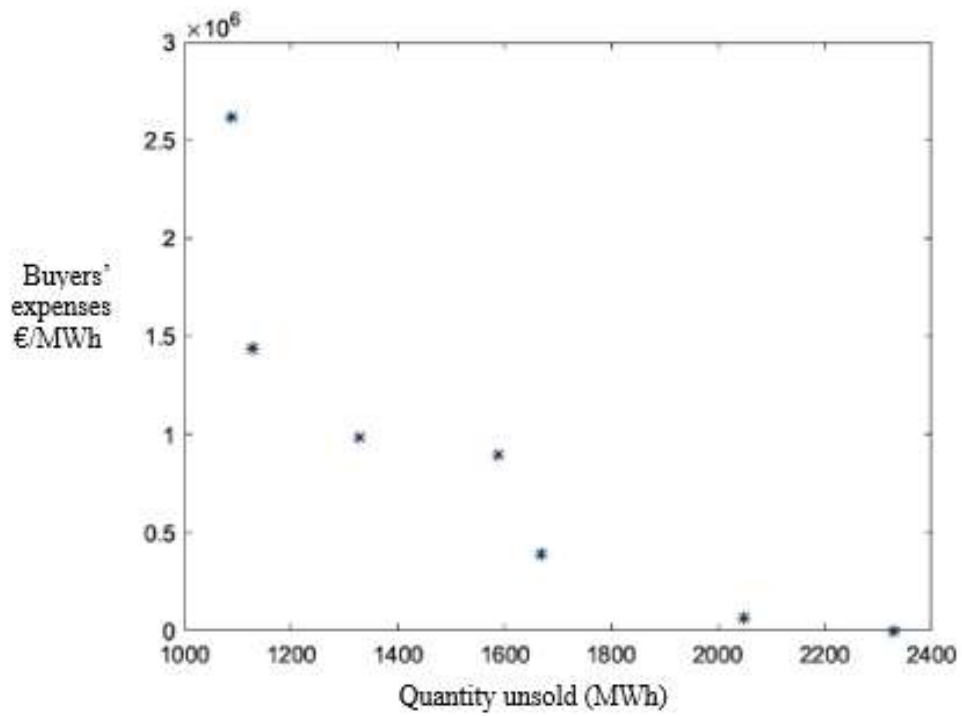


Figure 6.5: Pareto front resulting from the analyses

There are several Pareto optimal solutions, represented by the stars in the graph, which vary between two possible extremes:

- Not selling any energy and not buying any energy (thus no expenditure for the buyers).
- Selling all the energy at the maximum price that buyers are willing to pay.

Figure 6.6 shows the trend of match prices in the last market session studied by the genetic algorithm. The x-axis represents the progressive number of matched offers, while the y-axis shows the corresponding match prices.

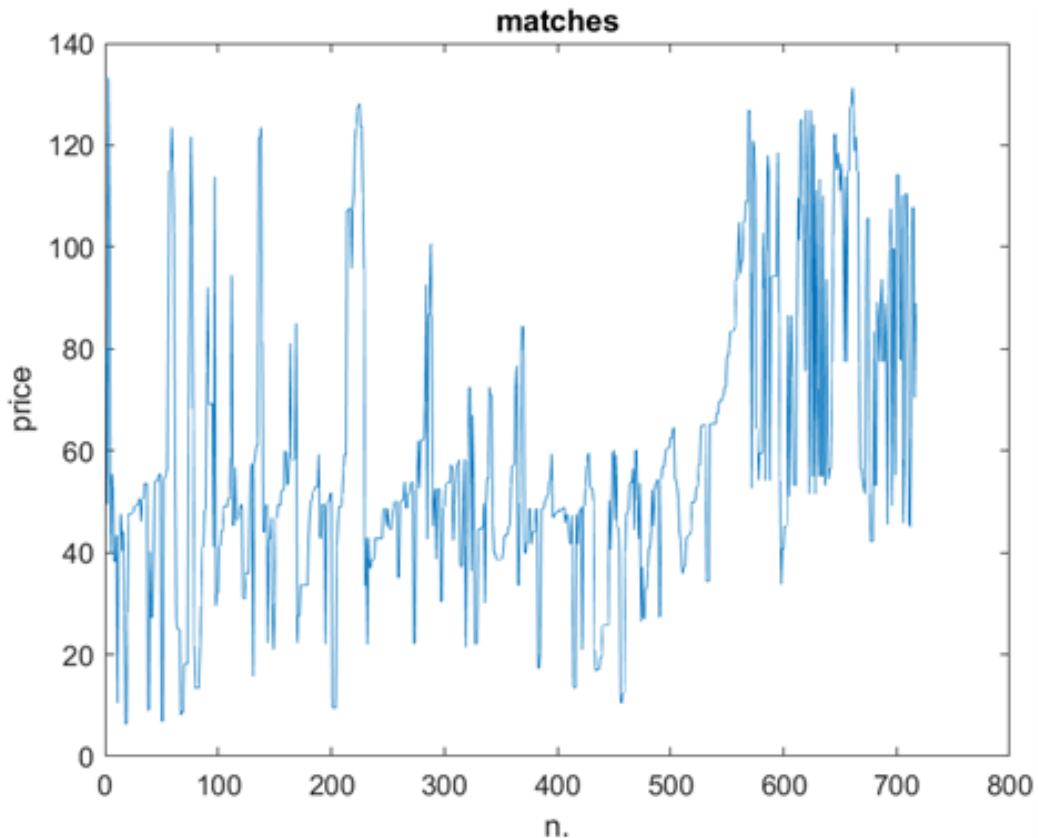


Figure 6.6: Match prices trend

We observe that initially, the volatility is high, but over time it decreases and then increases during the last stages of the market. This is a typical trend in intraday market prices [102]. Figure 6.7 and Figure 6.8 show the comparison between the welfare and the quantity not sold, both determined by the adaptive aggressiveness algorithm. In the first case, the algorithm is formulated as proposed by Vytellingum (referred to as AA), while in the second case, the aggressiveness parameter is reformulated using genetic algorithms (referred to as G.A.). The

analysis conducted with the use of genetic algorithms was performed multiple times, each time changing the objective functions. In particular, four analyses were conducted:

1. G.A.1: The welfare of both buyers and sellers is maximized individually, and the quantity not sold is minimized.
2. G.A.2: Only the welfare of buyers and sellers is maximized individually.
3. G.A.3: The total welfare is maximized, and the quantity not sold is minimized.
4. G.A.4: The welfare of both buyers and sellers is maximized individually, and the total welfare is also maximized.

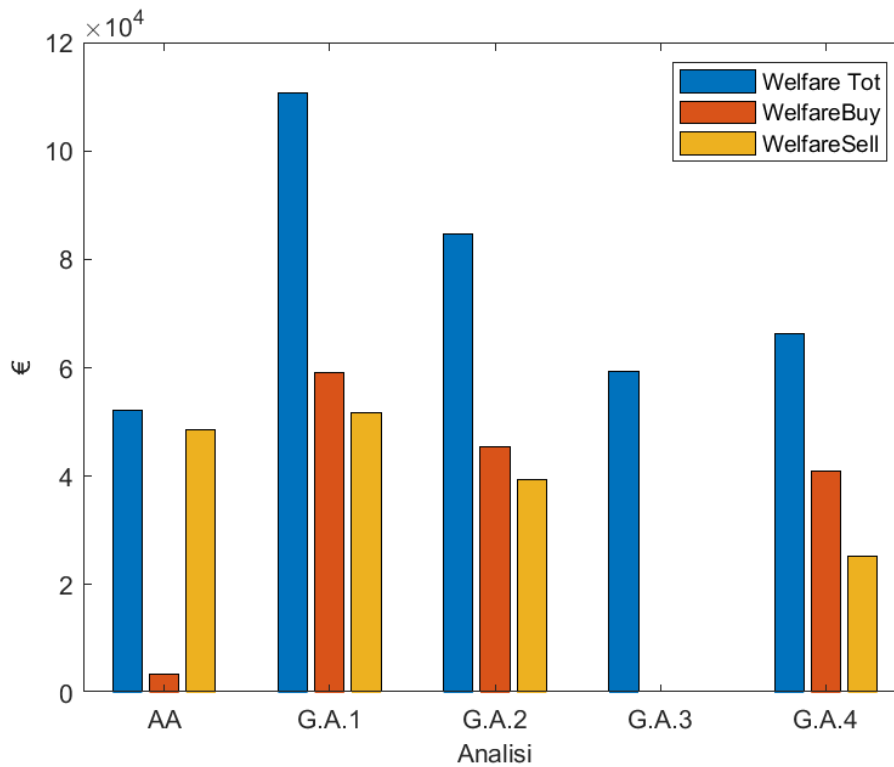


Figure 6.7: Comparison of welfare for different analyses

In Figure 6.7, it can be observed that regardless of the implemented objective function, the total welfare of the system always achieves higher values when using genetic algorithms. The adaptive-aggressiveness method rewards only certain agents (in this case, the sellers) at the expense of others, affecting the overall total welfare. However, specific actors may achieve very good results in terms of profit margin with respect to the offering prices and quantity not sold. This is because the adaptive-aggressiveness method lacks a mechanism that describes

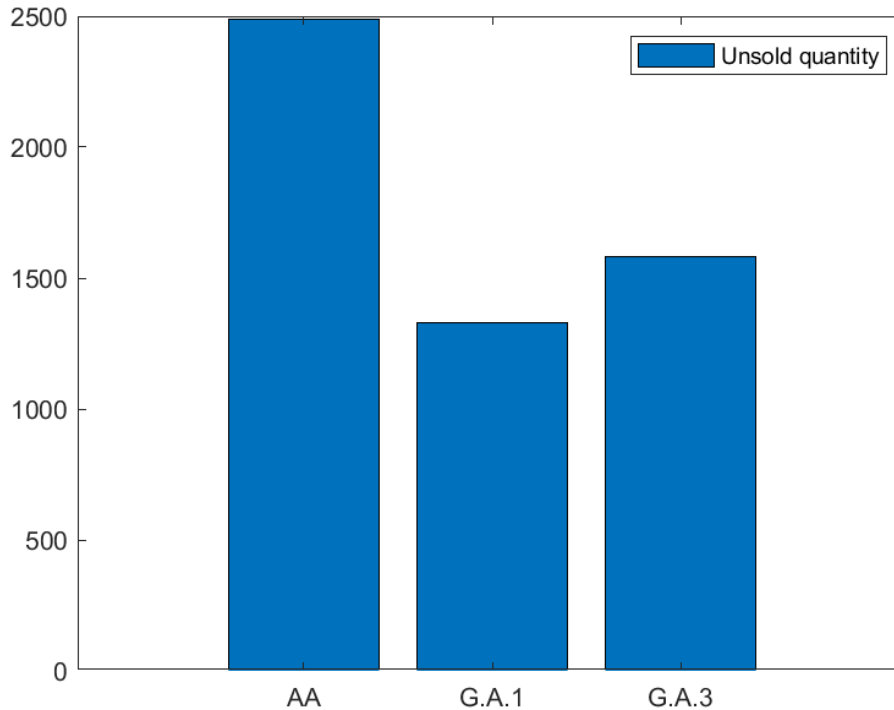


Figure 6.8: Comparison of unsold volume for different analyses

the sequence in which agents present their bids, and thus, it is possible that a certain agent may be called upon to present bids more frequently than another, allowing them to refine their strategy more precisely than their rivals. As a result, only a few agents may obtain excellent profits from the market. With genetic algorithms, the welfare is better distributed among market participants, and consequently, the overall total welfare increases considerably. Additionally, in Figure 6.8, it is noticed that the quantity not sold is significantly lower when using genetic algorithms. This occurs because setting the objective function to minimize imbalances distributes the aggressiveness of various agents in such a way that all of them can enter the market by selling or buying the necessary energy. While the use of genetic algorithms considerably improves different market results, it is challenging in a real-world scenario for agents to combine their strategies in a way that each one benefits from the market without imposing on others. Moreover, all the algorithms explained and analyzed so far do not consider external events, such as possible equipment failure or unforeseen changes in weather conditions that cause variations in energy production for non-programmable energy sources. Given the progressive increase in the penetration of non-programmable renewable energy generation, it is crucial to implement a model capable of replicating the results of continuous trading while taking into

account the uncertainty brought by such sources. In the next section, an innovative continuous trading market model based on the strategies commonly used by managers of programmable and non-programmable power plants will be presented.

6.3 New Agent-Based Model for Continuous Energy Trading in the Intraday Market

In this chapter, we present a market model where agents place orders based on three fundamental aspects to faithfully reproduce the results of the continuous intraday electricity market:

- The technology used to generate energy.
- Information derived from past transactions.
- External information affecting the market.

The following paragraph provides a precise description of the characteristics of continuous trading that we aim to replicate through the model.

6.3.1 Main Characteristics of Continuous Trading Market Replicated by the Model

The most significant features of continuous trading market observed through statistical analysis of orders placed by participants in some European markets [24] [22] include:

1. Agents predominantly use the hours closest to the delivery time to place offers, and the frequency of offer presentation increases as the market closing hour approaches.
2. Orders can be classified based on the technology of the generation facility. Agents with programmable facilities (e.g., thermal power plants) tend to place offers close to their marginal costs and keep their offers in the order book even if there is no immediate match. They decide whether to offer to buy or sell by comparing their marginal costs with the market price. If the market price is higher than their marginal costs, they try to

sell energy; otherwise, they attempt to buy it. Non-programmable energy sources (e.g., wind and solar power plants) present offers based on production forecasts. If they predict an increase in production compared to the previous day's market, they try to sell excess energy; otherwise, they attempt to buy. Since they must close the session with a balanced position, they present sell offers at very low prices and buy offers at very high prices to ensure a match. If they do not find an immediate match, they immediately withdraw their offer to avoid the risk of incurring high expenses or receiving low revenues due to the functioning of the matching algorithm.

3. The market price variation is strongly influenced by the participation of renewable energy sources. Specifically, an increase in renewable energy results in price decreases, while the opposite leads to price increases.
4. The continuous trading market is efficient in satisfying the buying and selling demands of operators while minimizing imbalances [103]. A model, therefore, should be capable of reproducing this characteristic. In mathematical terms, this means that the price trend reflects the property of martingales [104]:

$$E|P_{t+\Delta t}|F_t| = E|P_t|F_t|.$$

Here, $E|\cdot|$ represents the expected value, $P_{t+\Delta t}$ is the martingale value at time $t + h$, and F_t represents the set of information available at time t . The formula states that the expected value of a certain stochastic process at time $t+\Delta t$, given all available information at time t , is equal to the expected value at time t , knowing the same information.

In the next paragraph, we present the mathematical model on which the simulation algorithm is based.

6.3.2 Mathematical model

The model presented here aims to realistically replicate the behaviors described above. We assume that only rational agents operate in the modeled market. Consider N agents divided

into two groups: N_{fuel} agents equipped with programmable thermal power plants, and N_{res} agents equipped with non-programmable renewable energy sources. Thus, $N = N_{\text{fuel}} + N_{\text{res}}$. Let the n -th agent have a quantity $q_{t,n}$ already sold or bought in the market at time t . The vector of traded quantities at time t is denoted as $q_t = (q_{t,1}, q_{t,2}, \dots, q_{t,N})$. On the other hand, the vectors $q_t^{\min} = (q_{t,1}^{\min}, q_{t,2}^{\min}, \dots, q_{t,N}^{\min})$ and $q_t^{\max} = (q_{t,1}^{\max}, q_{t,2}^{\max}, \dots, q_{t,N}^{\max})$ indicate the minimum and maximum quantities that each agent can sell or buy to remain balanced. For example, for a plant with a capacity of 100 MW and flexibility to decrease production until shut down, we have $q_{t,n}^{\min} = 0$ and $q_{t,n}^{\max} = 100$. For a renewable energy plant, $q_{t,n}^{\max}$ is a variable dependent on weather conditions. It is important to highlight that, in the case of considering possible plant malfunctions, $q_{t,n}^{\max} = 0$, and thus $q_{t,n}^{\max}$ becomes a random variable even for programmable plants. In such cases, the malfunctioning plant, unable to produce energy, will only re-purchase the energy it had sold in the previous day's market. For simplicity, we assume that each agent always presents offers with very low volumes (1 MWh). Therefore, if an agent has large quantities of energy to exchange, depending on the outcome of the previous day's market bargaining (explained in section 4.5), they must present multiple orders. This restriction is reasonable because, for market efficiency, multiple orders with reduced volumes generate lower price volatility compared to a single large-volume order [105]. This assumption can be easily eliminated without significant changes in the results. Given the nature of continuous trading, theoretically, all agents can place an order in each very small time interval (even less than a millisecond). However, in our model, we assume that each agent can decide whether to present an offer or not no less than 0.01 seconds after the last offer presented. Let $\tau_{s,n}$ be the time at which the s -th offer of the n -th agent is placed, and we initialize $\tau_{0,n} = 0$ s because all agents place an order at the beginning of the session to fill the order book. Therefore, we assume that the initial orders depend on the results of the previous day's market. Thus, all agents who had offers accepted in the previous day's market fill the order book with purchase orders, while those who did not have accepted offers fill it with sell orders. The initial offer price corresponds to the system marginal price from the previous day's market. Since each order has the same volume, the order book can be described with a pair of vectors that describe the order prices (B_t, S_t) , where $B_t = (B_{t,1}, \dots, B_{t,M_t^B})$ indicates the prices of buy orders and $S_t = (S_{t,1}, \dots, S_{t,M_t^S})$

indicates the prices of sell orders at time t . M_t^B and M_t^S indicate the corresponding positions of the orders in the order book. B_t is sorted in ascending order, while S_t is sorted in descending order with respect to price, so that $B_{t,1}$ is always the best buy offer (highest price), and $S_{t,1}$ is the best sell offer (lowest price). It is obvious that $B_{1,t} < S_{1,t}$ to avoid an immediate match. At the beginning of the session, the system marginal price obtained in the previous day's market separates the sell orders from the buy orders. A fundamental part of the algorithm is the temporal definition of the potential action of presenting an offer, $\tau_{s,n}$. Specifically, if, for example, an agent needs to sell 10 MWh of energy during the last 10 minutes of the market session, they will plan to sell 1 MWh per minute. But if the sell offer is not accepted, the agent will have to sell 10 MWh in 9 minutes, and therefore they will need to adjust their potential offer action by increasing the frequency of order placement. In general, we assume that each time an agent evaluates the possibility of placing an order, they immediately recalculate when to place the next order. Therefore, other agents are not allowed to change their potential action when an agent places their order, unless another agent is conditioned by an external event $e_{1,n}, \dots, e_{E,n}$, such as a malfunction or an update of weather forecasts. Given time t , we define the next event after time t as $e_n(t) = \min\{e_{i,n} | e_{i,n} > t, i = 1, \dots, E\}$. Thus, the potential action of presenting an offer for agent n at step s with a time fraction $\epsilon = 0.01$ is defined as: The potential action of an agent n at step s is defined as follows:

$$\tau_{s,n} = \min\{e_n(\tau_{s-1,n}), \tau_{s-1,n} + \delta_{s,n}\}$$

where

$$\delta_{s,n} = \begin{cases} \max\left\{\frac{T-\tau_{s-1,n}}{q_{\tau_{s-1,n},n}^{\max}-q_{\tau_{s-1,n},n}}, \epsilon\right\}, & \text{if } q_{\tau_{s-1,n},n}^{\max} > 0 \\ \max\left\{\frac{T-\tau_{s-1,n}}{q_{\tau_{s-1,n},n}-q_{\tau_{s-1,n},n}^{\min}}, \epsilon\right\}, & \text{if } q_{\tau_{s-1,n},n}^{\min} < 0 \end{cases}$$

where $\delta_{s,n}$ represents the time fraction for which agent n at step s wants to place their offer.

The two fractions become smaller as the numerator decreases, i.e., as the time of delivery approaches. Thus, we can define the following potential action of agent n at time t :

$$\tau_n(t) = \min\{\tau_{s,n} | \tau_{s,n} > t, s = 0, 1, \dots\}$$

There is a vector of potential actions for each agent $\tau(t) = (\tau_1(t), \dots, \tau_N(t))$, which defines which agent will be the next to place an order:

$$n(t) = \arg \min_{n=1, \dots, N} \{\tau_n(t)\}$$

Therefore, agent $n(t)$ at time $\tau_n(t)$ decides whether to place an order or not. Since all agents are rational, they make decisions based on several factors. Firstly, each agent aims to maintain the position declared at the end of the previous day's market. If they observe a potential increase (decrease) in energy, they will try to sell (buy) the excess (shortfall) energy. The order price depends on the marginal costs and the market price at that specific moment. For instance, if the marginal costs are higher than the market price, there is no reason to sell energy as the gains would be lower than the costs. Additionally, each agent presents offers aiming to maximize their profits. Renewable energy sources have zero marginal costs ($MC_{res} = 0$). If they observe an increase in energy, they will offer to sell it at the lowest possible price: $P = 0$ €/MWh, while if they observe a decrease in energy, they will offer to buy the missing energy at the maximum price: $P = P_{max}$. However, this does not mean that they will actually buy energy at the maximum market price or sell it at zero. According to the matching algorithm rules, the transaction price is determined by the price of the offer that has been in the order book for the longest time. Therefore, a "renewable" agent presents offers at the limit prices to ensure a match, but the transaction price will be the most competitive price available in the book at that moment. If the "renewable" agent cannot conclude the transaction immediately, they will withdraw the offer to avoid actually selling their energy at zero or buying it at P_{max} . On the other hand, a thermal power plant with precise production costs will present offers depending on its marginal costs and the market price (MP). If the marginal costs (MC) are higher than MP , the agent will seek to buy energy to remain balanced with the position declared at the end of the previous day's market, without having to produce it at their marginal costs but buying it at lower prices. If $MC \leq MP$, the agent will try to sell energy, making a profit: $R_n(t) = MP(t) - MC_n$. The decision to buy or sell energy also affects the quantity to be offered

q_n and, therefore, the priority in presenting an offer. For example, a thermal power plant that still has 20% of available capacity to sell in the intraday market will present orders with higher (lower) frequency if its marginal costs are higher (lower) than the market price. Furthermore, in the model, it is considered that a thermal power plant, after obtaining a match, can present an order opposite to the matched one. This assumption is implemented to simulate strategies adopted by operators to maximize their profits. If an operator who placed a sell (or buy) offer obtains a match, they make themselves available to buy (or sell) all or part of the just matched energy at prices that generate a profit on the final quantity of energy transacted.

6.3.3 Methodology for the Market Session Analysis

To gain a comprehensive understanding of the obtained results, we present the logic behind the conducted analyses for the market session. The model takes as input the output results from a defined test case for a DAM session involving 30 generators, referring to a single hour of the following day. Initially, marginal costs and maximum capacity values are assigned to each power plant 6.1, and a demand value to be satisfied is assumed. Using this data, the demand/supply curve is created (6.9), which determines which generators are accepted and excluded from the previous day's market. It is also assumed that each accepted generator decides to retain a portion of its total capacity in the hope of offering the remaining margin of capacity in the MI at higher prices to achieve higher profits. The simulation begins with the wind energy production forecasts that each renewable agent hypothesizes at different time intervals, as shown in Figure 6.10. The statistical formulation of these forecasts is presented in the next paragraph. Based on the different weather forecasts, renewable plants will present different offers to remain balanced, while thermal power plants will buy and sell energy, aiming to increase their profits. At the end of the session, each agent will have a different position from the initial one based on the energy sold or purchased during continuous trading. Figure 4.12 and Figure 4.14 respectively show the offers in the order book at each instant and the offers presented by operators (both those immediately matched and those stored in the book), allowing for the analysis of price trends and the study of operators' strategies in different hours of the market. In paragraph 4.5.2, the offers presented and the resulting order book from a

session in which a generator experiences a failure a few hours before the market closing are reported.

6.3.4 Results

In this section, we present the outcomes of a specific scenario comprising 30 agents ($N=30$), divided into 10 characterized by renewable facilities ($N_{res} = 10$) and 20 by thermal facilities ($N_{fuel} = 20$) with the features delineated in Table 6.1. As depicted in this table, it was assumed that the marginal costs of renewable facilities were zero, while assumptions regarding the marginal costs for thermal facilities were randomly selected by the model from a set of potential input values.

The simulation begins with the demand-supply curve derived from the previous day's market outcomes, which is essential for the algorithm's initialization. Figure 6.9 presents the aggregated volumes (blue circles) of each generator in ascending order (from least expensive to most expensive), while the market demand is represented by the black vertical line, indicating the total accepted volume. On the y-axis, the marginal costs of the various generators are plotted. The point of intersection between the demand curve and the supply curve divides the generators that were accepted in the previous day's market (to the left of the demand curve) from those excluded (to the right of the demand curve). Additionally, the corresponding y-axis value of the intersection point determines the system marginal price, which is the market price at which the continuous trading session begins.

The last generator accepted in the market is number 19, and therefore, the thermal generators 20 and 30 are excluded due to their marginal costs being higher than the market price. The initial market price is determined as $P_{market}^0 = 180/MWh$. Figure 6.10 illustrates the position of each generator at the beginning of the continuous trading session at $t=0$. The blue color represents the volumes already sold by wind power plants, while the red color indicates the remaining capacity potentially available for sale. Similarly, the yellow color and the purple color respectively denote the quantities already sold and the remaining ones for the thermal power plants.

All accepted thermal power generators from the previous day's market, nonetheless, decide

Table 6.1: Agent Characteristics

Agent MI	Type	Marginal Cost (/MWh)	Max Capacity (MW)
1	Wind	0	50
2	Wind	0	110
3	Wind	0	76
4	Wind	0	51
5	Wind	0	112
6	Wind	0	169
7	Wind	0	94
8	Wind	0	68
9	Wind	0	87
10	Wind	0	186
11	Coal	20	71
12	Coal	40	191
13	Coal	60	50
14	Coal	80	177
15	Coal	100	117
16	Coal	120	78
17	Coal	140	60
18	Coal	160	54
19	Coal	180	93
20	Coal	200	126
21	Natural Gas	19	163
22	Natural Gas	38	164
23	Natural Gas	57	195
24	Natural Gas	76	135
25	Natural Gas	95	79
26	Natural Gas	114	167
27	Natural Gas	133	181
28	Natural Gas	152	129
29	Natural Gas	171	74
30	Natural Gas	190	135

to retain a portion of their capacity to potentially sell it in the intraday market and enhance their revenues. The energy production of wind power plants corresponds to the prior forecast. The energy sold during the previous day's market aligns with the forecast for the start of the continuous market at time $t=0$. Once the continuous market commences, they update their production forecasts and submit buy and sell offers, aiming to maintain the positions declared at the end of the Day-Ahead Market (DAM). Figure 6.11 presents the forecasts generated by the 10 agents (wind power plants) regarding their production during the intraday market.

At the onset of the session, they forecast a certain energy production, but an increase in wind due to atmospheric conditions elevates their production projection. Consequently, the

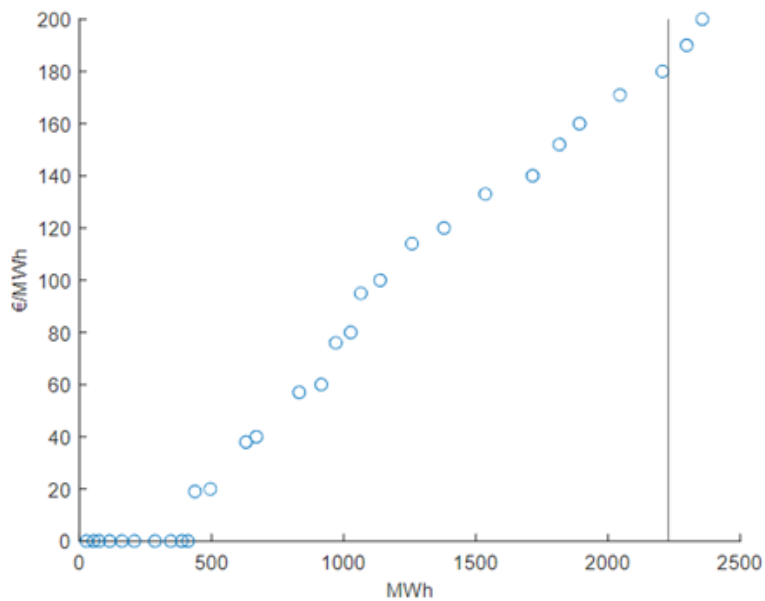


Figure 6.9: Supply-demand curve

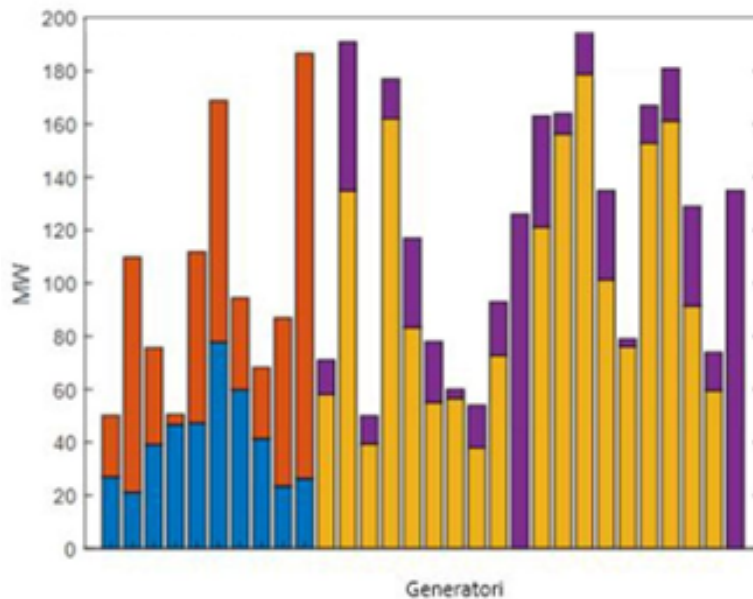


Figure 6.10: Volumes already sold by wind power plants (blue) and remaining capacity potentially available for sale (red); quantities already sold (yellow) and remaining quantities (purple) for the thermal power plants.

wind power plants will attempt to sell their energy, the higher-cost thermal power plants won't manage to enter the market, and some plants that were accepted during the previous day's market will decide to curtail their production by purchasing energy at a more advantageous price. Figure 6.12 illustrates the temporal evolution of the order book superimposed on the instantaneous market price. Selling offers are shown in red, while buying offers are displayed

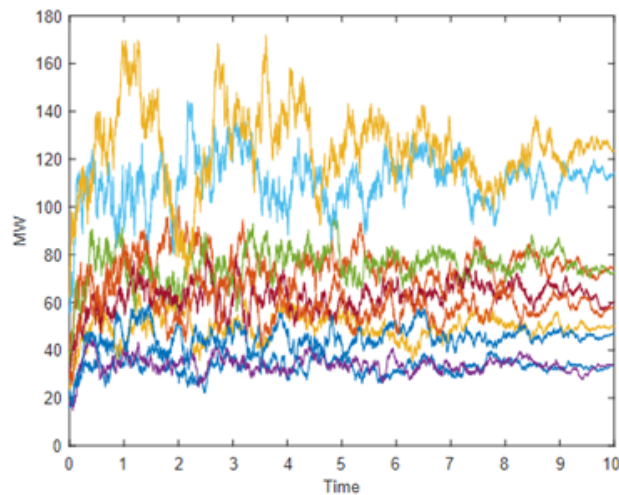


Figure 6.11: Variation of the forecasted energy production from wind power plants from the opening to the closure of the continuous trading session.

in blue. The x-axis represents the passage of time from the beginning of the session ($t=0$) up to one hour before delivery ($t=10$), while the y-axis depicts the prices of the offers present in the order book.

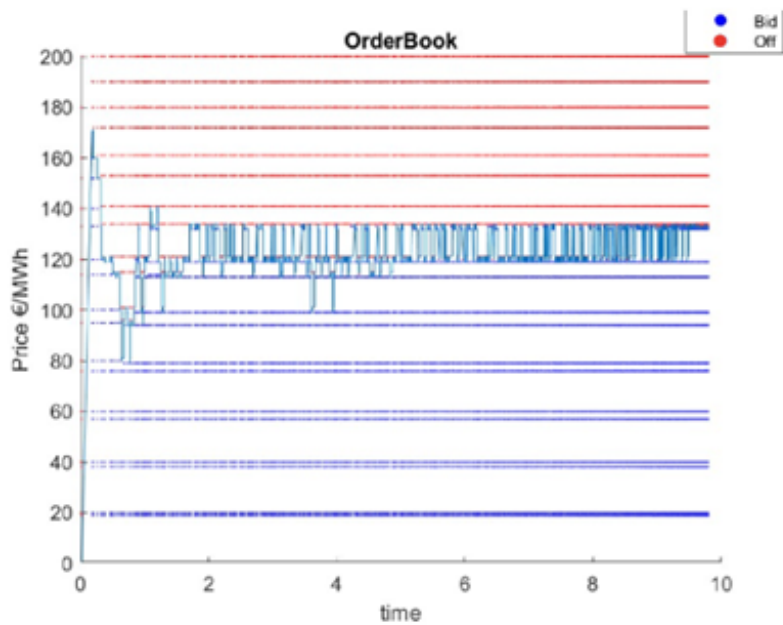


Figure 6.12: Evolution of the order book and market prices

The price curve starts from the initial system marginal price and decreases after a few hours, as expected. The density of offers increases as the market closure approaches because, as also observed in real-world scenarios, agents who were unable to buy or sell energy to balance their

positions must increase the number of their offers to avoid imbalances. Figure 6.13 illustrates the position of each generator at the end of the market ($t_f = T$). The colors correspond to the same parameters as shown in Figure 6.10.

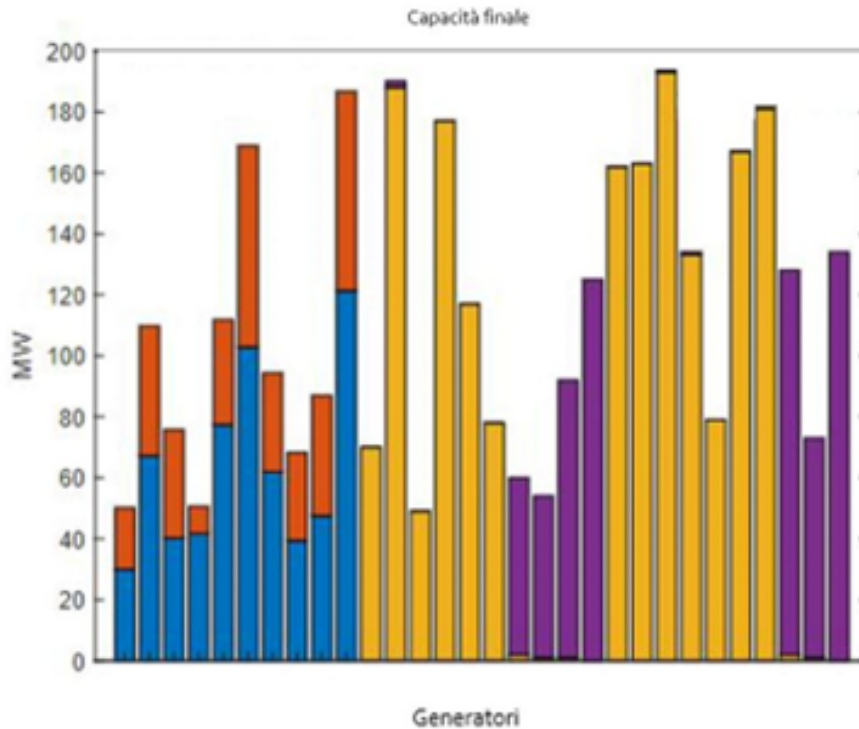


Figure 6.13: Volumes already sold by wind power plants (blue) and remaining capacity that can potentially be sold (red); quantities already sold (yellow) and remaining quantities (purple) of thermal power plants.

As anticipated, wind power plants increase their production to sell the excess energy to the more expensive thermal power plants, which prefer to buy rather than produce. The plants excluded from the previous day's market fail to sell energy even during the continuous trading, while thermal power plants with lower marginal costs manage to sell all the available energy. Figure 6.14 provides further insight into the behavior of various market participants and aids in analyzing their strategies, depicting each moment when each of the 30 agents submits an offer. Offers for purchase that immediately find a match are represented in blue, offers for purchase that do not find a match are shown in light blue, while offers for sale that immediately find a match are in red, and those that do not find a match are in violet.

Agents that consistently find an immediate match whenever they submit an order do not increase their frequency of action; this trend is clearly observable for Agent 11 and Agent 21,

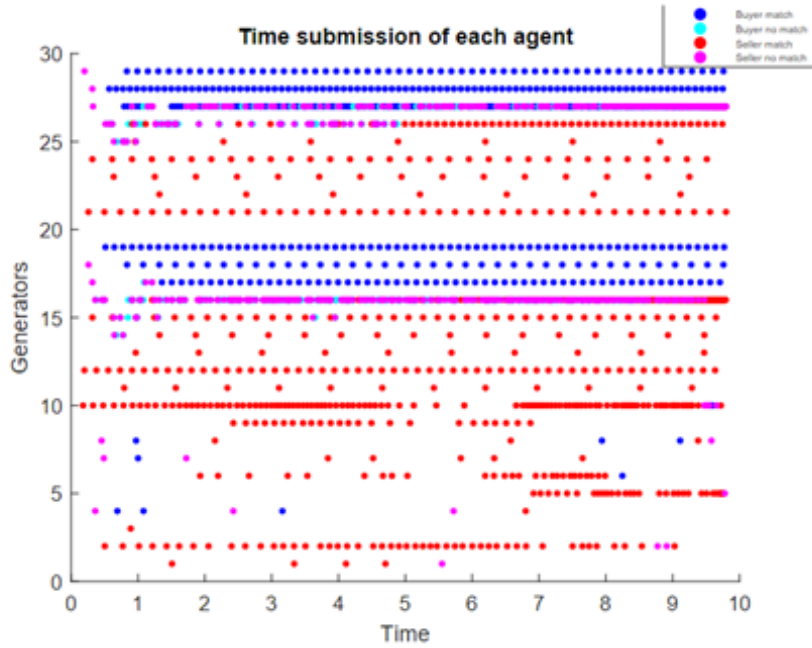


Figure 6.14: Instant of offer submission for each generator

which are the thermal generators with the lowest marginal costs. On the other hand, agents that do not find an immediate match to their offers increase their frequency of action as the session approaches its end, as seen with Agent 10 (wind) and Agent 27 (thermal). An interesting pattern emerges with thermal Agent 26, initially attempting to sell its energy without success, but when the market price slightly increases, it manages to sell its entire capacity. Thermal Agent 16, on the other hand, is most active during the final six hours of the market when the matching price aligns with its marginal costs (€120/MWh). However, it successfully sells its energy only in the last hour of the market, with the price hovering around €140/MWh.

Wind energy production forecast

The wind production used in the model (Figure 6.11) is defined through a stochastic process. Let us call $W_{(t,i)}$ the matrix composed of N_{res} rows and T columns, where N_{res} is the number of wind generators, and T is the number of updates (new production forecasts). At the beginning of the simulation, each renewable agent i has an initial expected production $E[W_{(0,i)}] = \mu_{(0,i)}$, which corresponds to the energy offered in the Day-Ahead Market. At the end of the session, they will have a different energy production forecast $W_{(T,i)}$ with the same expected value they had at the market opening $E[W_{(t,i)}] = E[W_{(0,i)}] | \mathcal{F}_t$. In particular, we assume for the first

column of the matrix a multivariate normal distribution of values around the initial value $W_0 = (W_{0,1}, \dots, W_{0,N_{\text{res}}})' \sim N_{N_{\text{res}}}(\mu_0, \Sigma_0)$ with the initial expectation $\mu_0 = (\mu_{0,1}, \dots, \mu_{0,N_{\text{res}}})$. During the trading session, a specific function called 'mean reversion' is considered to update the wind-related information: for each time interval t , the production forecast $\mu_{(t,i)} = E[W_{(T,i)} | \mathcal{F}_t]$ for a generator i approaches the energy production $\mu_{(T,i)} = E[W_{(T,i)}]$ at the end of the session (T). More precisely, we have:

$$W_{(t,i)} = \mu_{(T,i)} + \phi_t(W_{(t-1,i)} - \mu_{(T,i)}) + \epsilon_{(t,i)} \quad (4.10)$$

With a time-varying standard deviation given by $\sigma_t = 2\sqrt{\frac{T-t}{T}} + 2$, the time-dependent mean reversion given by $\phi_t = \frac{1}{2}\sqrt{\frac{T-t}{T}} + \frac{1}{2}$, and $\epsilon_{(t,i)} \sim N_1(0, \sigma_t)$. Thus, the mean reversion and standard deviation decrease as the delivery time approaches, resulting in more realistic forecasts.

Generator outage

It is also interesting to observe how prices and participants' strategies vary in the event of a generator failure. We present a scenario where the agents are the same as described earlier, but one of the low-cost thermal power plants experiences a breakdown two hours before the market closure. As a result, its production drops to zero, and it is compelled to buy all the energy it had declared at the end of the previous day's market. In Figure 6.15, we can observe this change occurring precisely during the 8th hour.

Focusing on row 12, it is evident that the plant immediately switches from selling to buying energy as soon as it experiences a breakdown, significantly increasing the frequency of offer submissions. Consequently, the market prices also experience a sharp increase at the time of the breakdown. Some operators, like thermal power plant 28, alter their strategy by deciding to sell their available volumes instead of buying. This decision is motivated by the fact that its marginal costs are €152/MWh, while the energy price after the breakdown rises to €160/MWh. This increase is depicted in Figure 6.16, which illustrates the price trend alongside the offers present in the order book.

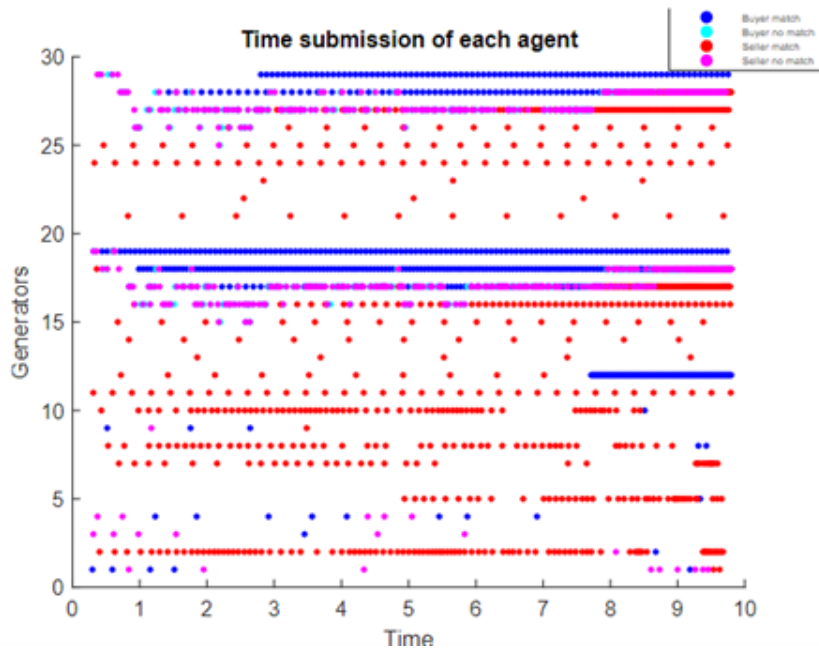


Figure 6.15: Instant of offer submission for each generator in case of an outage

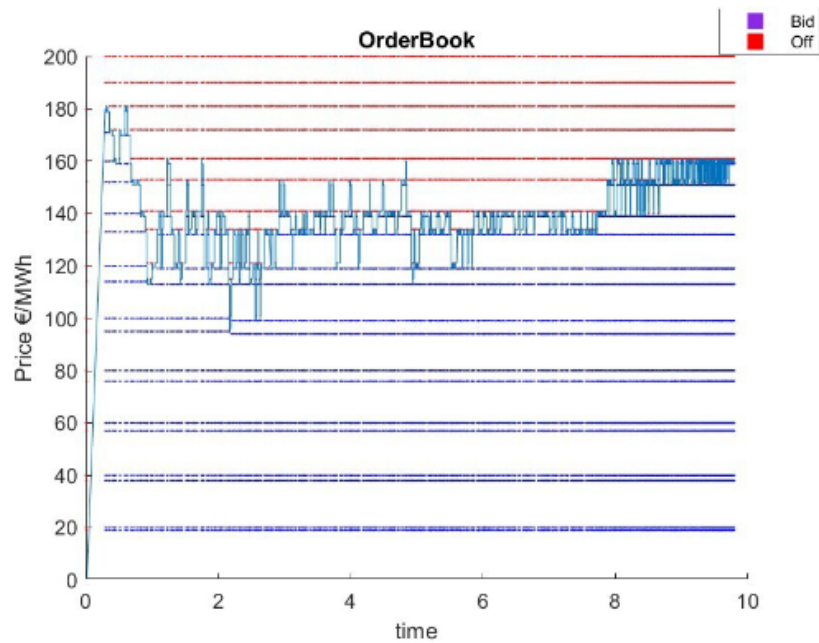


Figure 6.16: Evolution of the order book and market prices in the case where a thermal power generator experiences a breakdown at hour 8

Chapter 7

CONCLUSIONS

This study has conducted a comprehensive analysis of the European intraday electricity market, employing statistical methodologies and modeling techniques to shed light on its intricate workings. The findings of this investigation yield several noteworthy conclusions:

1. **Timing of Intraday Trading:** It has been observed that market participants engage in intraday trading activities primarily during the final 5 to 6 hours leading up to the real-time delivery. This suggests that the intraday market serves as a crucial platform for adjusting energy schedules close to the delivery time. This change will significantly impact the Italian electricity market. Agents will transition from an auction-based model, enabling them to trade energy up to 5 hours before the delivery time, to a hybrid model that allows trading up until one hour before real-time delivery.

2. **Day-Ahead Market Influence:** The day-ahead market plays a pivotal role in shaping intraday trading decisions. Price signals generated in the day-ahead market strongly influence intraday transactions, as the price trend during continuous trading closely follows that of the day-ahead auction. It is crucial to explore the median price rather than the mean prices. Agents should place bids at the median price to enhance their chances of finding a suitable match in alignment with the market price.

3. **High-Frequency Order Deletion:** Approximately 85% of the orders submitted are swiftly deleted in case of an unsuccessful match. This behavior can be attributed to automated trading strategies, possibly involving algorithmic trading, which capitalize on the high frequency of order submissions. Such strategies are driven by the matching algorithm's rules favoring agents

who match pre-existing orders.

4. **Small Volume, Multiple Orders:** Market participants tend to submit numerous orders with relatively small volumes of energy instead of opting for single large orders to fulfill their energy needs. This behavior serves to mitigate price volatility within the market.

5. **Diverse Strategies Based on Technologies:** Players in the market adopt varying strategies contingent upon their technology and operational constraints. Dispatchable power plants tend to submit orders at or near their day-ahead prices, deciding to sell or buy energy based on market price fluctuations relative to their marginal costs. Non-dispatchable players employ strategies aimed at balancing their energy portfolios by actively submitting both sell and buy orders. These players often initiate orders far from the delivery time to maximize potential profits, gradually adjusting prices as the session progresses.

6. **Linear Regression in Price Submission:** Some market players adhere to a linear regression approach for price submissions until a match is found. This method is employed to optimize profit potential.

7. **Optimal Match Time-frame:** Through extensive data analysis, it has been determined that the most favorable time frame for agents to secure matches with a reasonably high expectation of revenue is typically between 3.5 to 4 hours before the delivery time.

Building upon the insights garnered from historical data analysis, two agent-based models were developed to simulate agent behavior and market dynamics:

1. **Genetic Algorithm-Enhanced Vitellingum Model:** The first model replicates the Vitellingum strategy, recognized as one of the most effective strategies in existing literature. Genetic algorithms were applied to optimize the aggressiveness of agents, aimed at improving overall market welfare and reducing unsold energy quantities. The results demonstrated the superiority of the genetic algorithm-enhanced model over the standard Vitellingum strategy, despite the reality that real-world agents often prioritize profit over collective welfare.

2. **Agent-Based Model with internal and External Information:** The second model incorporates strategies derived from statistical analyses and supplements them with external data, such as forecasts of natural events. Agents are categorized as dispatchable and non-dispatchable power plants, each employing specific strategies based on market prices and weather conditions.

All agents have the capacity to conclude sessions in balance, and the market price adjusts in accordance with energy production forecasts and market dynamics. This model serves as a versatile tool for studying various scenarios and assessing the impact of different strategies employed by market participants. The impact of a power plant outage on energy prices is also assessed.

In sum, this study not only offers a deep understanding of the European intraday electricity market but also contributes valuable models and insights that can aid in optimizing market performance and decision-making processes.

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Appendix A

List of publications

CONFERENCE PAPERS

1. ‘Analysis of the SIDC market on relationship between auctions and continuous trading’
2021 AEIT international annual conference. A.Alberizzi, P. Grisi, A.Zani.
2. ‘Analysis of the intraday market: statistical analyses of German single intraday coupling’
2022 AEIT international annual conference. A.Alberizzi, P. Di Barba, A.Zani
3. ‘Statistical analysis of two different intraday market design: the German and Iberic intraday market’ 2022 EEM international conference of the European energy market.
A.Alberizzi, P.Di Barba, A.Zani, M. Pantos
4. J. C. Alberizzi, M. A. Pérez Estevez, M. Renzi, L. Jin, M. Rossi and A. Alberizzi, "Optimal Management of a Hydro – Wind Energy System with Hydrogen Storage," 2023 12th International Conference on Power Science and Engineering (ICPSE), Eskisehir, Turkiye, 2023, pp. 46-50

JOURNAL PAPERS

1. 'Impact Of Renewables Resources into The Italian Intraday Electricity Market' 2023 International Journal of Smart Grid and Clean Energy, vol. 12, no. 4, 2023: pp. 81-90
Submitted November 14, 2022; revised January 9, 2023; accepted June 10, 2023; published October 9, 2023. A.Alberizzi, P. Di Barba, A. Zani
2. Alberizzi, Andrea, Alessandro Zani, and Paolo Di Barba. "Analyzing the European Intraday Market: Statistical Insights and Strategies for Continuous Trading in Renewable Energy Systems." International Journal of Renewable Energy Research (IJRER) 13.4 (2023): 1515-1525.
3. Alberizzi, A., Di Barba, P., Mognaschi, M. E., Zani, A. (2024). Optimization of an agent-based model for continuous trading energy market. Electrical Engineering, 1-15.
4. 'Agent Based Modeling for Intraday Electricity Markets' OPSEACRH journal. A. Alberizzi, P. Di Barba, F. Ziel, A. Zani. (Still under review)
5. 'A new intra-day energy market model with auctions and continuous trading mechanisms' Proceedings of the National Accademy of Sciences, Physical Sciences. A. Alberizzi, P. Di Barba, A. Zani, M. Flammini (still under review)

PUBLICATIONS FOR THE NATIONAL RESEARCH ENERGETIC SYSTEM

1. 'Analyses of the Single Intraday Coupling (SIDC)' Deliverable RDS 2019-2021 for the national electric research system. Project 2.1: tools and models for energetics scenarios, analysis of market evolution and regulation. A.Alberizzi, P.Grisi
2. ' Analysis and Development of Models for the Simulation of the Continuous Energy Trading Market' ' Deliverable RDS 2022-2024 for the national electric research system. Project 2.1: tools and models for energetics scenarios, analysis of market evolution and regulation. A.Alberizzi

Appendix B

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