Analyzing the European Intraday Market: Statistical Insights and Strategies for Continuous Trading in Renewable Energy Systems

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Abstract- The global focus on climate change has led to policies aimed at reducing carbon emissions and integrating renewable resources into the energy system. As a result, the electrical energy market has undergone significant changes, including the adoption of continuous trading in the European intraday market. This model enables market agents to exchange energy close to the delivery time, addressing challenges related to renewable energy forecasting. This research provides a comprehensive analysis of the intraday market, examining the characteristics and behaviors of market players engaged in continuous trading. Statistical analyses, including density analysis, regression analysis, time-series analysis, and correlation analysis, are employed to investigate the relationship between submitted order prices and the trend price relative to the day-ahead market. The findings shed light on these market dynamics. Additionally, a novel strategy is proposed to optimize revenue by considering the probability of a successful match. This strategy assists market participants in maximizing profits while ensuring a reasonable chance of finding suitable trading partners. Overall, this research contributes to understanding the European intraday market, particularly continuous trading. The statistical analyses offer insights into market characteristics and player strategies. These findings have practical implications for market participants and policymakers, aiding in informed decision-making and efficient trading practices in the evolving energy landscape. The study's guidance assists stakeholders in navigating this dynamic environment, emphasizing the significance of renewable energy integration and continuous trading. By leveraging this research, stakeholders can enhance profitability, contribute to renewable resource integration, and make informed decisions in the energy market.

Keywords Energy market, statistical analyses, renewable energies, continuous trading.

1. Introduction

In recent years, there has been a global effort to reduce greenhouse gas emissions and combat the impacts of climate change [1]. As a result, the importance of renewable energy generation has significantly increased. Technologies such as solar, wind, hydro, and geothermal power plants offer cleaner alternatives to traditional fossil fuels, leading to a profound transformation in the global energy landscape [2]. However, the integration of renewable resources into the energy market presents unique challenges. Unlike conventional power sources like coal or natural gas plants, renewable genera-tion is heavily dependent on weather conditions and characterized by intermittent output [3]. The variability and unpredictability of renewable energy pose significant obstacles for grid operators in maintaining a reliable and stable electricity supply [4]. In this context, the intraday market plays a crucial role in addressing the intermittent nature of renewable energy generation and fulfilling the demand for electricity. These markets facilitate the trading of electricity in short intervals, typically ranging from a few hours to one hour before delivery, allowing market participants to adjust their energy portfolios in real-time [5]. By enabling grid operators and market players to trade electricity continuously, the intraday market provides an avenue to optimize strategies and mitigate the challenges posed by renewable energy integration [6]. One of the key aspects of the intra-day market is the opportunity for market players to implement strategies that enhance their revenue and operational efficiency. The dynamic nature of the market, with its short trading intervals, allows participants to adapt their trading decisions based on real-time information and market conditions [7]. This flexibility empowers renewable energy producers to capitalize on short-term fluctuations in energy prices, enabling them to optimize revenue by selling excess electricity during periods of high prices or purchasing additional electricity during periods of low prices [8]. Furthermore, market players can employ a variety of trading strategies to maximize their competitive advantage in the intraday market. These strategies may involve analyzing historical data, market trends, and price patterns to forecast future price movements and optimize bidding decisions [9] and [10]. Additionally, participants can leverage statistical analyses to gain insights into the behavior of market agents, suchas the number of orders submitted in different time frames, price volatility, liquidity concentration, and overall market dynamics [11] and [12]. By understanding these factors, market players can develop effective trading strategies that enhance their revenue and ensure a balanced and efficient energy market [13] [14]. This study aims to provide a comprehensive understanding of the strategies employed by various power plants operating in the continuous intraday market. By conducting in-depth statistical analyses on the Italian intraday market, this article explores several key considerations, including the temporal price trends, patterns of order submissions, price volatility, and liquidity concentration. Based on these findings, a novel bidding strategy is proposed in the later part of the paper. This strategy aims to maximize the welfare of market agents, defined as the difference between the profit obtained from selling energy and the cost of providing it [15]. Additionally, the strategy considers the probability of achieving a positive match within a specific timeframe. These two aspects have been analyzed in literature only separate like in [16] and [17]. The proposed method incorporates the temporal proximity between order submission and delivery time, a critical factor in continuous intraday trading [18]. The outcomes of the statistical analyses provide valuable insights into the behavior of market agents and shed light on the effectiveness of different strategies employed in the continuous intraday market. The article is structured as follows: Section two delves into the general characteristics of the intraday market and the continuous matching algorithm. Section three presents the statistical analyses carried out to study the behavior of market agents, with a specific focus on the strategies adopted by power plants. Section four highlights the results of these analyses, accompanied by insightful discussions. Finally, the conclusions are presented in section five.

2. Intraday Market

To comprehend the techniques utilized by market participants competing in the perpetual intraday market, the crucial first step is to provide a precise depiction of the market's key attributes and the uniform trading matching algorithm.

2.1. Market Characteristics

Within the European market, players are granted the ability to engage in continuous 24/7 trading of hourly products between countries, provided that there is sufficient transmission capacity available between the relevant bidding zones [19]. A two-module Integrated Determination (ID) solution facilitates this process, consisting of the Shared Order Book (SOB) and Capacity Management Module (CMM). The SOB is responsible for gathering all orders originating from Nominated Electricity Market Operators (NEMOs) and generating executable contracts for electricity trading. The CMM is responsible for managing and distributing transmission capacity between all bidding zones [20]. The characteristics of power markets and the matching algorithm employed are dependent on the specific product and contract of the orders. For example, the" hourly" product has a delivery period of one hour and includes information such as whether the order is a buy or sell, the price, quantity, and delivery hour. Orders may fall into one of three categories: regular, iceberg, or block [21].

- A regular order is an instruction issued by a market participant to buy or sell a specified amount of energy at a designated price with a limit, i.e., a minimum price for sell orders and a maximum price for buy orders.
- Iceberg orders are trading instructions that are only partially visible in the market, with a portion of their total quantity displayed, while the full quantity remains exposed for matching. These orders may also have a range of limit prices associated with them.
- A block order refers to an order for multiple predefined contracts that belong to the same product and have consecutive delivery periods.

For each order, different execution restrictions can be applied: NON (none), IOC (immediate or cancel), FOK (fill or kill), or AON (all or nothing). Only iceberg orders have no execution restrictions [18]. NON restrictions implies that the order can be executed immediately entirely or partially and the remain quantity enter in the order book. IOC restrictions implies that if the order is not executed immediately it is deleted by the system without entry in the order book. Partially matched ca also be allowed. FOK restrictions implies that the order is immediately and completely matched otherwise it is deleted by the system. AON restrictions implies that the order ca be only entirely executed otherwise it enters in the order book. Partially matches are not allowed. Once an order is submitted, it can be matched, partially matched, deleted or it can enter in the SOB. Enter in the SOB mince that the order is visible to other users until either it is deleted or matched with a new entry order. Orders can be matched between different market areas only if there is available transmission capacity. When a match occurs between orders from different market areas, the required transmission capacity for the transaction is allocated by the CMM. Orders are ranked in the SOB with a deterministic process based on a price-time merit order [22]. Sell and buy orders are ranked with the best price first so, highest to lowest price for buy orders and lowest to highest price for sell orders. If two orders enter the same price, the oldest one gets the priority.

2.2. Matching Algorithm

Order matching is a fundamental process in trading that leads to the execution of a trade. In order to be matched, buy and sell orders must originate from opposite sides and pertain to the same contract. A trade can only be executed if the price of a sell order is equal to or below the price of a buy order, and vice versa. The execution of orders follows the price-time merit order, where the best sell order is matched with the best price order. In the case of orders with the same price, priority is given to the order with the oldest time stamp [23]. Once a match occurs, the quantity of the orders is reduced by the trade quantity, unless the orders have execution restrictions such as Fill-or-Kill (FOK) or All-or-None (AON), in which case the order must be fully matched or not matched at all. When two orders are matched, one of them must be a new entry order while the other must already exist in the order book. The price of the transaction is determined by the price of the order already stored in the order book. For instance, if a new buy order is matched with an existing sell order, the buyer must pay the price corresponding to the sell order, and the seller receives the corresponding payment for their submission. A new entry order may be matched with multiple existing orders in the order book, each presenting different prices. Once the order is matched with the best-priced order in the opposite direction, the existing order with the best price level is updated, and the matching process continues. This process persists as long as the incoming order remains executable and has a positive order quantity.

3. Analyses Developed

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

3.1. 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 [24]. 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. [25]. So, A variable X has density f_x:

$$P[a \leq X \leq b] = \int_a^b f_x(x)dx \tag{1}$$

The probability density function for the order submission in relation to the delivery timeframe 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 timeframe. 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:

$$P[X] = (1-p)^{k-1}p \tag{2}$$

Where p is the probability of a successful event.

3.2. 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 [26] 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:

$$Cor = \frac{\sum_i (r_i - \bar{r})(s_i - \bar{s})}{\sqrt{\sum_i (r_i - \bar{r})^2}\sqrt{\sum_i (s_i - \bar{s})^2}} \tag{3}$$

Where r and s are the two parameters to be correlated

3.3. Time-Series Analyses

This analysis focuses on the time series pattern of data to assess the price trend of the continuous market [27]. 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:

$$Y_i = \beta_0 + \beta_1 X_1 + \epsilon_i \tag{4}$$

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.

3.4. Regression Analysis

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:

$$Y_i = f(X_i, \beta) + e_i \tag{5}$$

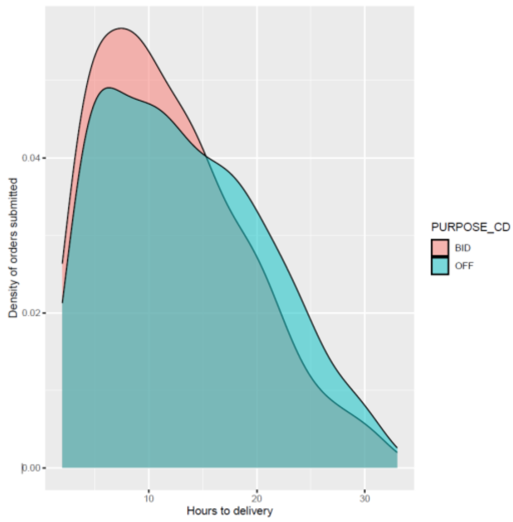
$f(X_i, \beta)$ is a function that most closely fits the data, e_i is the error term that is not directly observed in order to investigate the relationship between the price of orders over time, a regression analysis was conducted. Regression models are commonly used to forecast changes in prices over 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. Results

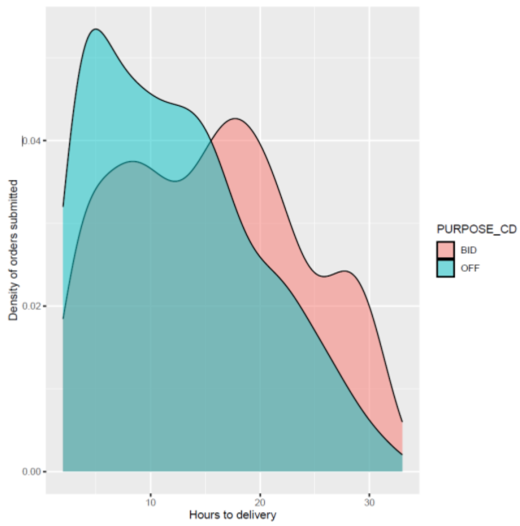
The present section reports the outcomes of the statistical analyses conducted. The analyses focused on two specific days of the year 2022, namely October 20 and April 10, and although other days were examined, the results obtained from these two days are deemed to be sufficiently significant to depict 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.

4.1. Orders Submissions

The density function described in section 3.1 identifies the preferred time frame for continuous trading by market agents. Fig. 1 illustrates the relationship between the density of submitted orders (y-axis) and the time-distance (x-axis).



(a)



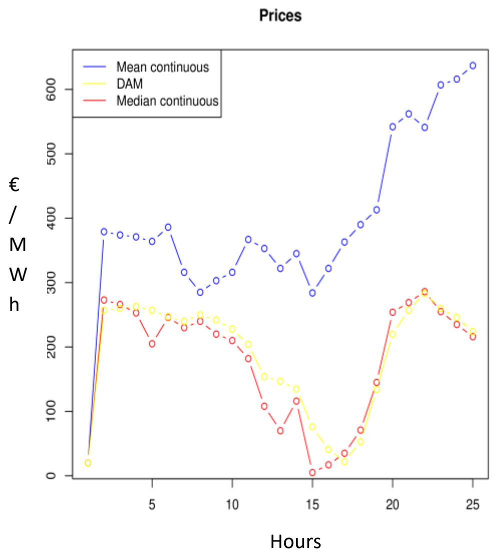
(b)

Fig. 1. 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.

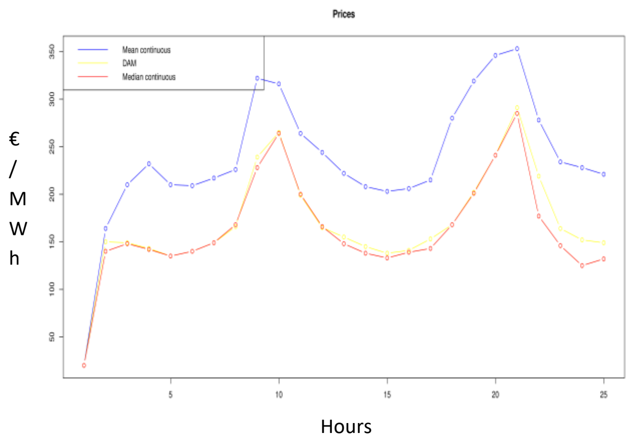
The plotted density curves of bids and offers exhibit a unimodal and right-skewed distribution, except for bids submitted in October. This indicates that the majority of orders are submitted near the delivery time, while only a small proportion are submitted more than 10 hours in advance. The peak of 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.

4.2. 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, Fig. 2 illustrates the daily price trend of the day-ahead market auction alongside the mean and median prices of orders submitted during continuous trading.



(a)



(b)

Fig. 2. 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 Fig. 2 the mean prices of continuous trading do not always follow the dam prices as the media values do. In table 1 and 2 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

Tab 1. 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

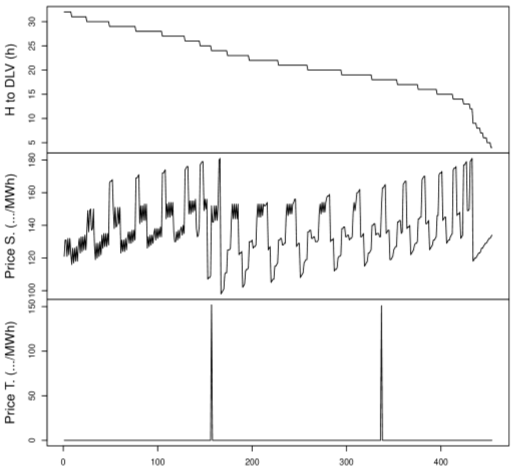
Tab 2. Correlation prices for the 10 October 2022

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.

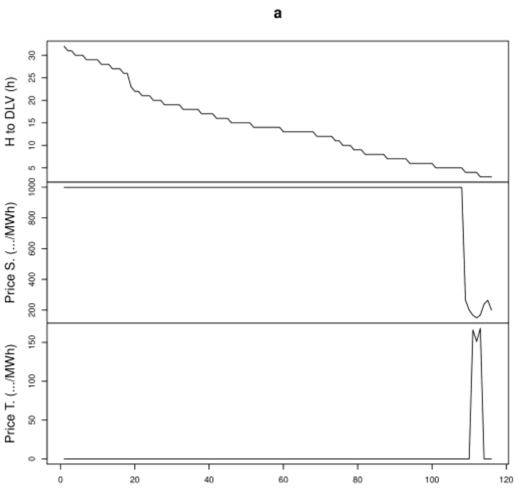
4.3. Prices in Relation to the Delivery Time

It is essential to examine the price trend with respect to the time gap between the submission and delivery times. Figure 3 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.

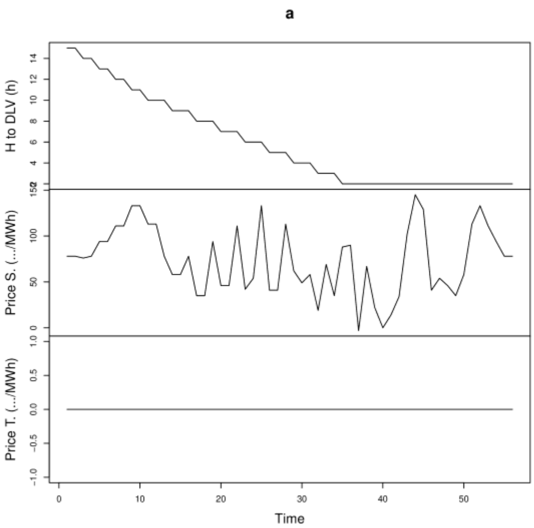
a



b



c



d

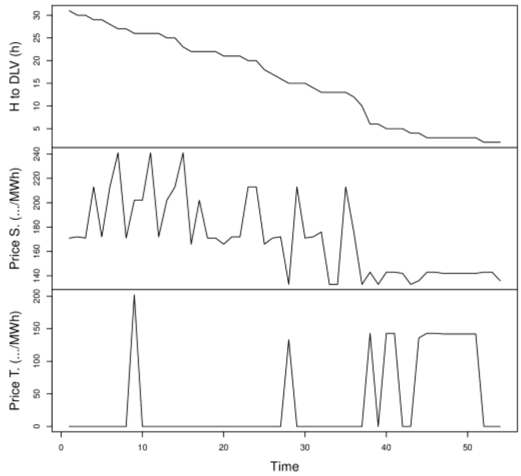
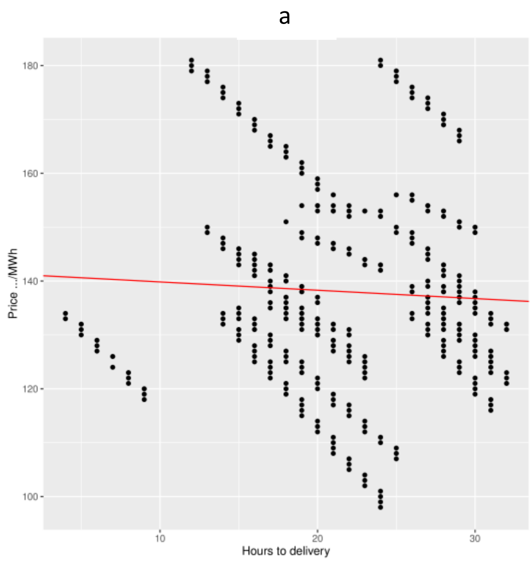


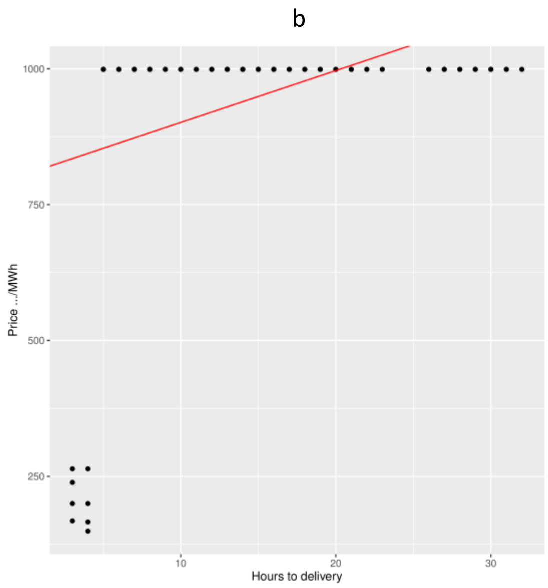
Fig. 3. Time series of price in relation to the distance between the submission and delivery time fora solar (a), hydro (b), h (c) and thermo-electric (d) power plant.

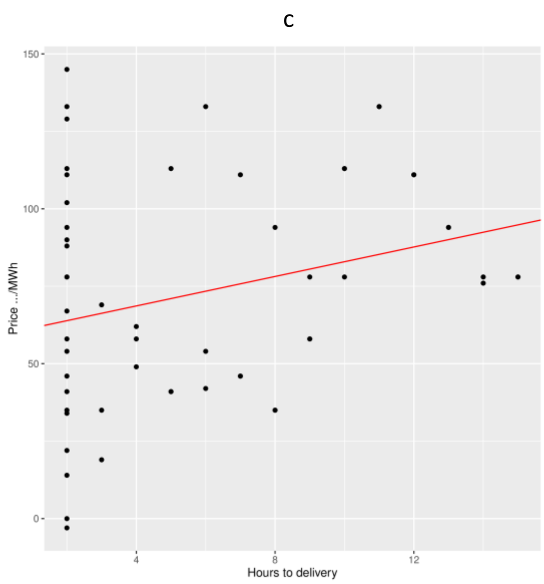
Plot a shows the bidding strategy employed by a solar power plant for purchasing energy. Initially, it submits low-priced bids and gradually raises the offered price as the delivery time approaches. Upon finding a successful match, it repeats the same trend, starting with a low price and increasing the 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.

4.4. Price Forecast

In this analysis, a regression function was developed to forecast the price trend for the four different power plants. Fig. 4 presents the relationship between the orders price and the distance to the delivery time, overlaid with the regression line.







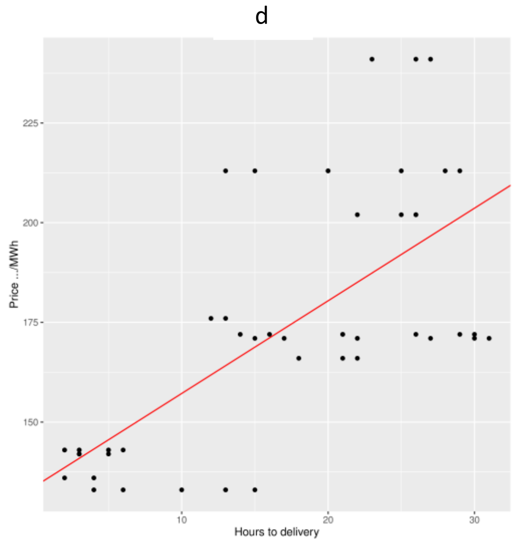


Fig. 4. Regression of price in relation to the distance between the submission and delivery time for a solar (a), wind (b), hydro (c) and thermo-electric (d) power plant.

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-electric (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.

4.5. Relations Between Submission 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 5 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.

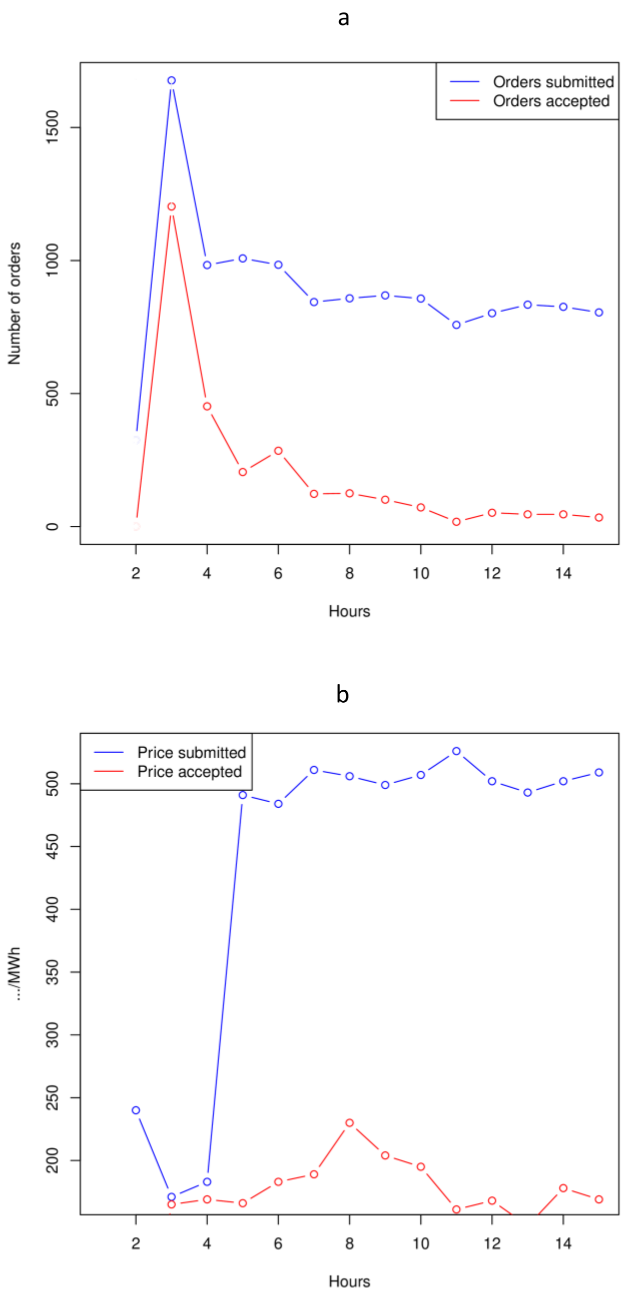


Fig. 5. Number of orders submitted and accepted (a) and Price of orders submitted and accepted (b) in relation to the delivery time distance.

The observed plot shape in figure 5.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 5.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 rolein determining price volatility, as shown in figure 6.

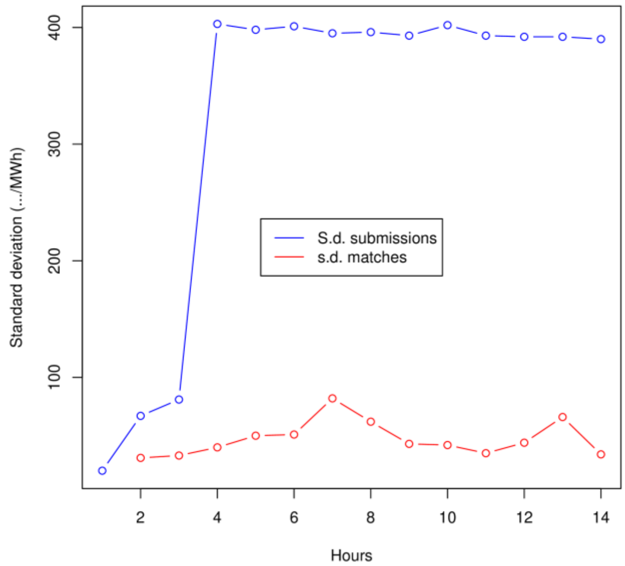


Fig. 6. Standard deviation of submission and match prices

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.

4.6. 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, whichis characterized as the ratio of orders that obtain a match over the aggregate number of submissions:

$$AR = \frac{O_{acc}}{O_{sub}} * 100 \tag{6}$$

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 submissionand acceptance price.

$$RE = \frac{\mu_{Ps}}{\mu_{Ps}-\mu_{Pa}} * 100 \quad (7)$$

Where μ_{PS} and μ_{Pa} 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 7 the trend of the acceptance rate (AR) of the submission and revenues expectations (RE) is built in relations to the distance to the delivery time.

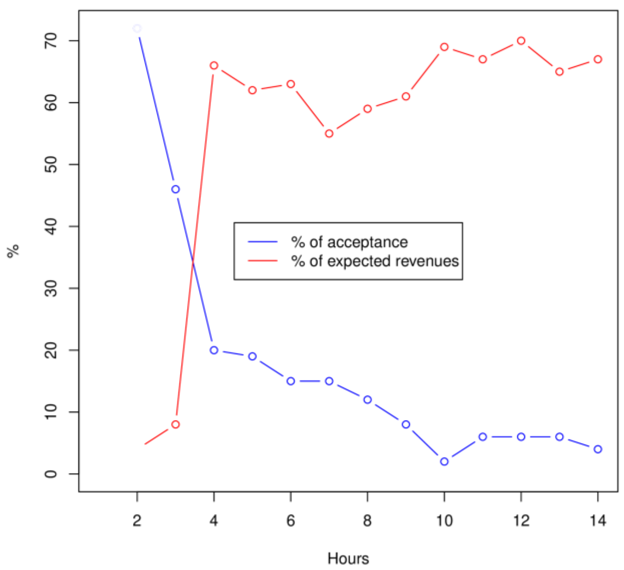


Fig. 7. Acceptance rate and expected revenues in relations to the delivery time distance.

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 timeframe during which agents have a high probability of finding good revenue matches. Prior to this point (i.e., the right part of plot 7), finding a match is challenging due to low order volumes and significant price volatility, but it is also the timeframe 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.
In summary, the proposed strategy seeks to identify the optimal timeframe during which market agents have a higher likelihood of finding profitable matches. This is achieved by carefully considering two key parameters: the acceptance rate and the expected revenues. By analyzing these parameters, the strategy takes into account the dynamic nature of the market as the delivery time approaches. By leveraging the acceptance rate, the strategy provides insights into the likelihood of orders being matched with suitable counterparts. This allows market participants to gauge the level of competition and the availability of trading opportunities within specific timeframes. Additionally, the strategy incorporates the expected revenues parameter, which considers the relationship between the average price of submitted orders and the margin between submission and acceptance prices. This provides valuable information on the profitability of different bidding decisions and helps market agents make informed choices regarding their pricing strategies. Overall, this approach offers a comprehensive understanding of market dynamics, market participant behavior, and the profitability of various trading strategies. By effectively identifying the optimal timeframe for bidding, market participants can increase their chances of securing profitable matches and achieving their revenue objectives in the continuous intraday market.

5.Summary Results

In general, the results reveal that the continuous energy market exhibits two distinct phases. During the first phase, which occurs more than 5 hours before the delivery time, market agents submit a limited number of orders in an attempt to maximize their revenues (for sellers) or minimize expenses (for buyers). The mean price of the submitted orders does not follow the mean of the matched prices, and there is a high level of price volatility indicated by a large standard deviation. In contrast, the standard deviation of the matched prices is significantly lower, and the mean price closely follows the market price with minimal volatility. In this phase, the median price emerges as a useful statistical parameter for formulating bidding strategies. Its trend aligns with the price signal from the day-ahead market and reflects the mean and median prices of the matched orders.

The second phase of the market occurs during the final 4 hours of the trading period. In this phase, agents submit a large number of orders with prices close to the market price, leading to a substantial increase in the number of matches. The discrepancy between the submitted and matched orders decreases significantly, and the standard deviation of both submission and match prices coincides. Close to the delivery time, agents are compelled to exchange energy to avoid penalty imbalances. As a result, they submit offers around the market price, even at the risk of earning smaller revenues, in order to increase the likelihood of finding a match.

Between these two phases lies a timeframe where agents can strategically bid to strike a profitable compromise. They seek to achieve a good chance of finding a match while generating substantial revenues relative to the cost of energy.

Different market participants adopt varying strategies based on their technologies. Non-dispatchable power plants, such as wind farms, attempt to sell energy at a high price during the early stages of the market session and only submit offers close to the market price in the final hour. This strategy is primarily due to the difficulty of accurately forecasting wind conditions far from the delivery time. Solar power plants, on the other hand, consistently submit offers throughout the market session, gradually increasing the price for purchasing energy as the delivery time approaches until a match is found. Dispatchable technologies generally submit offers around the market price, analysing the price trends and making decisions regarding selling or buying energy based on a comparison with production costs.

6.Conclusion

In conclusion, this paper provides an overview of the recent design of the European intraday market, with a specific emphasis on the continuous trading form. It also presents 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 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.

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References

[1] A. Mikhaylov, N. Moiseev, K. Aleshin, and T. Burkhardt. Global climate change and greenhouse effect. Entrepreneurship and Sustainability Issues, 7(4):2897, 2020.

[2] O. Ellaban, H. Abu-Rub and F. Baalbierg. Renewable energy resources: Current status, future prospects and their enabling technology. Renewable and sustainable energy reviews, 39:748-746, 2014.

[3] P Ravestein, G Van der Schrier, R Haarsma, R Scheele, and M Van den Broek. Vul- nerability of european intermittent renewable energy supply to climate change and climate variability. Renewable and Sustainable Energy Reviews, 97:497–508, 2018.

[4] G. Notton, M.L. Nivet, C. Voyant, C. Paoli, C. Darras, F. Motte, and A. Fouilloy. Intermittent and stochastic character of renew- able energy sources: Consequences, cost of intermittence and benefit of forecasting. Renewable and sustainable energy reviews, 87:96–105, 2018

[5] P. Sorknæs, A.N. Andersen, J. Tang, and S. Strøm. Market integration of wind power in electricity system

balancing. Energy Strategy Reviews, 1(3):174–180, 2013

[6] E. Bitar, P. P Khargonekar, and K. Poolla. Systems and control opportunities in the integration of renewable energy into the smart grid. IFAC Proceedings Volumes, 44(1):4927–4932, 2011.

[7] Jé. Bottieau, L. Hubert, Z. De Grève, F. Vallée, and Jean-François Toubeau. Very-short-term probabilistic forecasting for a risk-aware participation in the single price imbalance settlement. IEEE Transactions on Power Systems, 35(2):1218–1230, 2019.

[8] M. R Sarker, H. Pandžić, and M. A Ortega-Vazquez. Optimal oper- ation and services scheduling for an electric vehicle battery swapping station. IEEE transactions on power systems, 30(2):901–910, 2014.

[9] C. Kiekintveld, J. Miller, P. R Jordan, and M. P Wellman. Forecasting market prices in a supply chain game. In Proceedings of the 6th inter- national joint conference on Autonomous agents and multiagent systems, pages 1–8, 2007.

[10] A. Colak, & K. Ahmed (2021, September). A Brief Review on Capacity Sizing, Control and Energy Management in Hybrid Renewable Energy Systems. In 2021 10th International Conference on Renewable Energy Research and Application (ICRERA) (pp. 453-458). IEEE.

[11] F. McGroarty, A. Booth, E. Gerding, and VL R. Chinthalapati. High frequency trading strategies, market fragility and price spikes: an agent-based model perspective. Annals of Operations Research, 282:217–244, 2019.

[12]N. Altin, & S.E. Eyimaya, (2021, September). A Review of Microgrid Control Strategies. In 2021 10th International Conference on Renewable Energy Research and Application (ICRERA) (pp. 412-417). IEEE

[13]O. Alkul, D. Syed, & S. Demirbas, (2022, June). A Review of Wind Energy Conversion Systems. In *2022 10th International Conference on Smart Grid (icSmartGrid)* (pp. 72-77). IEEE.

[14]K. Okedu, & N. Nwazor (2023). Investigation of the Impact of Soot on the Efficiency of Solar Panels using a Smart Intelligent Monitoring System. International Journal of Smart Grid-ijSmartGrid, 7(1), 1-14.

[15]M. Khorasany, Y. Mishra, and G. Ledwich. "Hybrid trading scheme for peer-to-peer energy trading in transactive energy markets." IET Generation, Transmission & Distribution 14.2 (2020): 245-253.

[16]F. Le Floch, I. Gruia, Y. Rebours, & Y.V. Makarov (2016). Review of Models and Tools for Trading Strategies on Energy Markets. Renewable and Sustainable Energy Reviews, 56, 1007-1023.

[17]G. Diamantopoulos, A. Themistoklis, L. Symeonidis, and A. C. Chrysopoulos. "Designing robust strategies for continuous trading in contemporary power markets." Agent-Mediated Electronic Commerce. Designing Trading Strategies and Mechanisms for Electronic Markets: AMEC and TADA 2012, Valencia, Spain, June 4th, 2012, Revised Selected Papers. Springer Berlin Heidelberg, 2013.

[18]U. Cetinkaya, & R. Bayindir, (2022, June). Impact of Increasing Renewable Energy Sources on Power System Stability and Determine Optimum Demand Response Capacity for Frequency Control. In 2022 10th International Conference on Smart Grid (icSmartGrid) (pp. 396-400). IEEE.

[19]K. Neuhoff, N. Ritter, A. Salah-Abou-El-Enien, and Philippe Vassilopou- los. Intraday markets for power: Discretizing the continuous trading. 2016.

[20]C. Kath. Modeling intraday markets under the new advances of the cross- border intraday project (xbid): Evidence from the german intraday market. Energies, 12(22):4339, 2019.

[21]N. Graf von Luckner, A Cartea, S. Jaimungal, and Ru Kiesel. Op- timal market maker pricing in the german intraday power market. House of Energy Markets and Finance, Essen, Germany, 2017.

[22]A. Alberizzi, P. Grisi, and A. Zani. Analysis of the sidc market on relationship between auctions and continuous trading. In 2021 AEIT International Annual Conference (AEIT), pages 1–5. IEEE, 2021.

[23]S. Hagemann. Price determinants in the german intraday market for electricity: An empirical analysis. Journal of Energy Markets, 2015.

[24]A. Alberizzi, A. Zani, P. Di Barba, and M. Pantoš. Statistical analysis of two different intraday market designs: the german and iberic intra-day market. In 2022 18th International Conference on the European Energy Market (EEM), pages 1–6. IEEE, 2022.

[25]A. Alberizzi, A. Zani, & P. Di Barba, (2022, October). Analysis of the intraday market: statistical analysis of German single intraday coupling. In *2022 AEIT International Annual Conference (AEIT)* (pp. 1-6). IEEE.

[26]C. M. Grinstead and J.L. Snell. Conditional probability–discrete conditional. Grinstead & Snell's introduction to probability Orange Grove Texts, 2009.

[27]L. Myers and M. J. Sirois. Spearman correlation coefficients, differences between.Encyclopedia of statistical sciences, 12, 2004.

[28]J. D Cryer. Time series analysis, volume 286. Duxbury Press Boston, 1986.