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Agent-Based Model to Simulate Multiple Delivery Products in Continuous Intraday Electricity Market

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Abstract—The increasing variable renewable energy sources in the power system have led to rise in the trading volumes in the electricity markets. In this paper, we extend an existing open source agent-based model for simulating the behavior and interactions of the renewable, consumer, thermal, and market operator agents in the continuous intraday (CID) electricity market by introducing the energy storage agents. Furthermore, the limitation of the earlier model to account for the CID trade of a single delivery product is relaxed by extending the model to consider the simultaneous trading of all the possible delivery products in a day. A realistic trading behavior is enabled by an user-defined parameter for the thermal and storage agents to choose the switching point in the trading timeline when the strategy of the trading agent navigates from increasing their profits by trading in the CID market to avoiding any imbalances by considering their physical constraints. Comparative case studies are performed to demonstrate the evolution of the trading behavior of the agents throughout the trading horizons for multiple delivery products with different switching instances.

Keywords—Agent-based modeling, Continuous Intraday Electricity market, Energy storage

I. INTRODUCTION

The increasing variations in electricity generation due to the growing amount of variable renewable energy sources have resulted in an upsurge in trading activity in the short-term electricity markets. The intraday (ID) electricity market is one of the short-term markets that enable the market participants to trade based on their updated forecasts after the closure of the day-ahead market. In Europe, there are two types of ID electricity markets, continuous and discrete ID markets. The continuous intraday (CID) market is based on the continuous double auction (CDA) mechanism which adopts a pay-as-bid pricing scheme [1]. The discrete ID market is based on a merit-order dispatch mechanism where the market clearing takes place at a pre-specified time and all the buyers and sellers that are cleared in the market get a uniform price [2].

The Single Intraday Coupling (SIDC) project in Europe allows cross-border CID trade between 23 European countries as of November 2021. It has led to an increase in the market liquidity making it a lucrative trading avenue for traders across Europe. The volume traded in the ID market in Europe through EPEX SPOT has increased from 47 TWh in 2014 to 111 TWh in 2020 [3]. The SIDC project is based on the CID market mechanism, which is the major focus of our work. Most of the research work on the CID market so far assumes the participants to be price-takers and are limited to a single participant’s behavior in the CID market. The trading of energy storage in the CID market is modeled using a deep reinforcement learning framework in [4] and [5]. A multistage stochastic programming problem is formulated in [6] to model the trading behavior of a portfolio of wind, thermal, and hydropower in the CID market which is solved using a Stochastic Dual Dynamic Programming (SDDP) approach. Some recent works that also model energy storage in the CID market using a multistage stochastic optimization approach include [7] and [8]. However, the aforementioned works either neglect or consider to a limited extent the market impact of each player. In [9], the need to design models to study the interaction between multiple participants in the CID market is highlighted.

The first attempt to simulate the CID market as a CDA to study the influence of forecast error of the renewable agent on the market was made in [10]. However, in their work, the renewable agent is assumed to be a price-taker and a single entity that aggregates the entire wind and solar power generation and trades the overall forecast error in the CID market. An open-source agent-based model (ABM) is proposed in [11], to model and analyse the trade in the CID market between multiple agents and study their interactions. It also proposes adaptive learning strategies for the agents. However, that model is limited to simulating the CID trade only for one delivery product (DP), which is the time of delivery of electricity. Also, the earlier model only accounts for the renewable, thermal, and consumer agents.

In this paper, we contribute towards the existing open source agent-based model in the following ways:

- We extend the ABM to model the behavior of storage agents together with renewable, consumer, thermal, and market operator agents.
- We propose an extended framework to model the CID trade simultaneously for all the possible DPs in a given day.
- A user-defined parameter is introduced for thermal and storage agents to choose the switching point in the trading timeline. It decides when the strategy of the trading agent navigates from increasing their profits to avoiding any imbalances by considering their physical constraints. The physical constraints include the ramping limits for the thermal agents and the maximum charging and discharging rates for the energy storage agents.
II. BACKGROUND OF CID MARKET

The CID market the gate-opening (GO) takes place at 15:00 CET for the cross-border trading through the SIDC platform. It is possible to trade until the gate closure (GC) which is a few minutes before the real-time delivery of electricity. The delivery hour of electricity is referred to as delivery product (DP). As it can be seen from Fig. 1, it is possible to trade simultaneously for multiple DPs. In the European CID market, there are quarterly, half-hourly, and hourly DPs available for trading [12]. The power exchange (market operator) maintains a shared order book (SOB) which contains order information with their prices and volumes. For further details about the CID market mechanism, the readers can refer to [11].

Figure 1: Illustration of ABM with different agents trading in various electricity markets (GO: Gate-open, GC: Gate-close, DA: Day-ahead, RT: Real Time, IS: Imbalance Settlement).

III. OVERVIEW OF THE EARLIER ABM

As seen in Fig. 1, we model the CID trade of thermal, renewable, consumer, and storage agents for multiple delivery products. The agents post their orders in the CID market at a given frequency. Each order comprises price, volume, and side (buy or sell). Once these orders are received by the market operator (MO) agent, it arranges the buy (bid) and sell (ask) orders according to their prices. Then it clears the ask orders that are posted at a price less than or equal to bid order prices and vice versa for the bid orders. The information about the cleared orders is provided to the agents and the remaining orders are assumed to be canceled from the SOB.

The volume to be posted by any given agent is decided by the available capacity of generation or consumption and generation/consumption forecasts for the renewable and consumer agents. With the possibility to trade simultaneously in the CID market for multiple DPs, it is essential to coordinate the ramping constraints of the thermal agent. With the addition of the storage agent in the ABM, we also propose a method to calculate the volume traded by the storage agent. The modeling of renewable and consumer agents can be directly extended for multiple DPs from the single DP version as introduced in [11].

The price strategy decides how the price-volume curve is constructed considering the input values of the volume. This work utilizes two strategies, naive and modified trader adaptive aggressiveness (MTAA) both these strategies are described in [11]. The naive strategy randomly chooses prices in between the best ask and bid prices. The MTAA strategy is inspired by the adaptive aggressiveness strategy proposed in [13] for the stock market. The main feature of this strategy is the notion of aggressiveness, which decides the behavior of an agent in the market. A more aggressive trader aims to get transacted by submitting orders that are better than its estimate of competitive equilibrium price.

IV. MODEL DESCRIPTION

In this work, we inherit all the features described in section III and the extensions to it, including the detailed modeling of the thermal and storage agents participating in the CID market, are elaborated in this section. The modeling of the renewable and consumer agents in the ABM with multiple DPs is assumed to be similar to the single DP model in [11].

A. Thermal agent trading for multiple delivery products

While considering multiple DPs in the ABM, the trading volume posted by the thermal agent in the CID market needs to comply with its ramping limits. However, the GO of the CID market takes place several hours before the real-time delivery of electricity. If the ramping limits are considered throughout the CID trading timeline, it will significantly restrict the trading decisions of the thermal agent. Therefore, we divide the trading timeline into two parts at $t^{i}_{sd}$ (switch instance). In the first part, we relax the ramping limits of the thermal agents allow them to trade in the CID market whereas, in the second part of the timeline, it trades by considering the ramping constraints.

Figure 2: Example of positions of a thermal agent across delivery products visualized with ramp constraints

The ramping-up and ramping-down of generation across DPs are relative with respect to the DP in consideration. An example is provided in Fig. 2 where we assume the ramp-up and ramp-down capabilities of a thermal agent is 100 MW each and the sum of DA and CID market positions of the agent are represented on the Y-axis. The bars on each DP show the ramp constraints. In Fig. 2(b), the ramping-down
constraint between the first and second DPs and the ramp-up constraint between second and third DPs are violated. We establish a relation to identifying the DP due to which the ramping constraints could be violated, for example, the second DP in this case. The position of the thermal agent corresponding to second DP is rectified as per Algorithm 1.

**Algorithm 1** Ramp-up and ramp-down constraints algorithm

1. If $t \leq t^i_{d,t}$
2. $\delta_{i,t,d} \leftarrow \min\{C_i - p^\text{mar}_{i,t,d}, 0\} + \min\{p^\text{mar}_{i,t,d} - \Xi_i, 0\}$
3. Else
4. $\mu^i_t = \sum_d p^\text{mar}_{i,t,d}$
5. Initialize $\delta^h_{i,t,d} = 0$
6. If $|p^\text{mar}_{i,t,d} - \mu^i_t| \geq |p^\text{mar}_{i,t,d+1} - \mu^i_t|$
7. $\delta^h_{i,t,d} \leftarrow p^\text{mar}_{i,t,d+1} - p^\text{mar}_{i,t,d} - r^{\text{up}}$
8. Else
9. $\delta^h_{i,t,d} \leftarrow p^\text{mar}_{i,t,d} - p^\text{mar}_{i,t,d+1} - r^{\text{dn}}$
10. $\delta^h_{i,t,d} \leftarrow p^\text{mar}_{i,t,d+1} - p^\text{mar}_{i,t,d} - r^{\text{up}}$
11. Else
12. $\delta^h_{i,t,d} \leftarrow p^\text{mar}_{i,t,d+1} - p^\text{mar}_{i,t,d} - r^{\text{dn}}$
13. Else
14. $\delta_{i,t,d} \leftarrow \max\{p^\text{mar}_{i,t,d-1} - p^\text{mar}_{i,t,d} - r^{\text{dn}}, \delta^h_{i,t,d}\}$
15. Else
16. $\delta_{i,t,d} \leftarrow \min\{p^\text{mar}_{i,t,d-1} - p^\text{mar}_{i,t,d} + r^{\text{up}}, \delta^h_{i,t,d}\}$
17. $\delta_{i,t,d} \leftarrow \min\{p^\text{mar}_{i,t,d-1} - p^\text{mar}_{i,t,d} + r^{\text{up}}, \delta^h_{i,t,d}\}$
18. Else
19. $\delta_{i,t,d} \leftarrow \min\{p^\text{mar}_{i,t,d-1} - p^\text{mar}_{i,t,d} + r^{\text{up}}, \delta^h_{i,t,d}\}$
20. Else
21. $\delta_{i,t,d} \leftarrow \min\{p^\text{mar}_{i,t,d-1} - p^\text{mar}_{i,t,d} + r^{\text{up}}, \delta^h_{i,t,d}\}$
22. Else
23. $\delta_{i,t,d} \leftarrow 0$

The imbalance level of a thermal agent is decided based on its trading time in CID market. If the time-step is before the time of activation of ramping constraints then the imbalance is calculated according to Step 2 in Algorithm 1. However, if the time-step is after activating ramping constraints then the Steps 4 to 23 apply. For example, in Step 6, the difference is noted between the position ($p^\text{mar}_{i,t,d}$) of the thermal agent $i$ at time-step $t$ for a given DP, $d$ and mean ($\mu^i_t$) of the positions of that agent for all the DPs. In absolute terms, if the position ($p^\text{mar}_{i,t,d}$) deviates more from $\mu^i_t$ as compared to $p^\text{mar}_{i,t,d+1}$ then the position $p^\text{mar}_{i,t,d}$ needs to be modified. Furthermore, it is checked if the thermal agent needs to ramp-up or ramp-down for a particular DP as per Steps 7 and 9 respectively. The imbalance $\delta_{i,t,d}$ is set according to Step 8 or 10 depending on whether the thermal agent needs to ramp-up or ramp-down. Similarly, the approach followed for $d$ with respect to $d = 1$ is described in Steps 11 to 21. If neither of the conditions in Steps 6 or 11 applies then the imbalance is set at 0.

The volume decisions for the ask order ($\hat{v}^A_{i,t,d}$) and bid order ($\hat{v}^B_{i,t,d}$) to be posted by the thermal agent are governed by the Equations (1) and (2) respectively if the trading time is before the ramping constraints are activated:

$$\hat{v}^A_{i,t,d} = \min\{C_i - p^\text{mar}_{i,t,d}, \gamma^W_i \cdot r^{\text{up}}\}$$

$$\hat{v}^B_{i,t,d} = \max\{p^\text{mar}_{i,t,d} - \Xi_i, 0\}, \gamma^W_i \cdot r^{\text{dn}}\}$$

where $\gamma^W_i$ is a scaling factor to allow the agents to trade their volumes gradually in the CID market. For the trading time after activating ramping constraints, equations (3) and (4) determine the volume posted by the thermal agent:

$$\hat{v}^A_{i,t,d} = \min\{\max\{p^\text{mar}_{i,t,d} - \Xi_i, 0\}, \gamma^R_i \cdot r^{\text{up}}\}, \gamma^W_i \cdot r^{\text{dn}}\}$$

$$\hat{v}^B_{i,t,d} = \max\{r^{\text{dn}}_i, |\delta_{i,t,d}|\}, \max\{\max\{p^\text{mar}_{i,t,d} - \Xi_i, 0\}, \gamma^R_i \cdot r^{\text{up}}\}, \gamma^W_i \cdot r^{\text{dn}}\}$$

B. Storage agents in the CID market

The energy storage agent provides liquidity in the CID market and can also benefit from the changes in the market prices throughout the trading horizon. However, it has some limitations on the energy content ($E_{i,t,d}$), charging ($r^{ch}_{i,t}$) and discharging ($r^{dc}_{i,t}$) rates. Similar to the thermal agent, the storage agent is assumed to ignore these constraints up to a certain point of time ($t^i_{d,t}$) in the trading timeline, and the charging rate limitations are imposed after a given time. Algorithm 2 describes this behavior of the storage agent.

If the estimate of equilibrium price for the storage agent is $\hat{\pi}_{i,t,d}$ at $t$ for $d$ then the volume weighted average price ahead ($vwp^a_{i,t,d}$) is given by:

$$vwp^a_{i,t,d} = \frac{\sum_d P_{i,t,d} \cdot \hat{\pi}_{i,t,d}}{\sum_d P_{i,t,d}}$$
Algorithm 2  Storage trading volume decision algorithm

1: Initialize $\delta_{i,t,d} \leftarrow 0$
2: if $t \leq t_{i,t,d}^*$
3:   $\delta_{i,t,d} \leftarrow \min\{C_i - p_{i,t,d}^{\text{mar}}, 0\}$
4: else if $t_{i,t,d}^* < t \leq 0.5 \cdot (T - t_{i,t,d}^*)$
5:   if $\pi_{i,t,d} > v_{i,t,d} a p^a$ & $\sum_{d=1}^{d_{i,t,d}} E_{i,t,d} - \sum_{d=1}^{d_{i,t,d}} p_{i,t,d}^{\text{mar}} > C_i$
6:      $\delta_{i,t,d} \leftarrow \sum_{d=1}^{d_{i,t,d}} E_{i,t,d} - \sum_{d=1}^{d_{i,t,d}} p_{i,t,d}^{\text{mar}} - C_i$
7: else if $\pi_{i,t,d} < v_{i,t,d} a p^a$ & $\sum_{d=1}^{d_{i,t,d}} E_{i,t,d} - \sum_{d=1}^{d_{i,t,d}} p_{i,t,d}^{\text{mar}} < C_i$
8:      $\delta_{i,t,d} \leftarrow \sum_{d=1}^{d_{i,t,d}} E_{i,t,d} - \sum_{d=1}^{d_{i,t,d}} p_{i,t,d}^{\text{mar}} - C_i$
9: else
10:   $\delta_{i,t,p} \leftarrow 0$
11: else if $0.5 \cdot (T - t_{i,t,d}^*) < t \leq T$
12:   $\mu_i^p = \sum_{t=1}^{T} \frac{E_i}{T}$
13: Initialize $\delta_{i,t,d} = 0$
14: if $|\pi_{i,t,d} - \mu_i^p| \geq |p_{i,t,d+1}^{\text{mar}} - \mu_i^p|$\n15:   $\delta_{i,t,d} \leftarrow \min\{\delta_{i,t,d+1} - r_i^c + \gamma_i^c, 0\}$
16: if $p_{i,t,d+1}^{\text{mar}} \geq p_{i,t,d+1}^{\text{mar}} + r_i^c$\n17:   $\delta_{i,t,d} \leftarrow \min\{\delta_{i,t,d+1} - r_i^c, 0\}$
18: $u_i^a = |\delta_{i,t,d} > \min\{\delta_{i,t,d} \cdot r_i^c, \delta_{i,t,d} - |\delta_{i,t,d}|| |\delta_{i,t,d} > 0\}$
19: $d_i = |\delta_{i,t,d} > \min\{\delta_{i,t,d} \cdot r_i^c, 0\}$
20: if $p_{i,t,d}^{\text{mar}} - \mu_i^p \leq |p_{i,t,d-1}^{\text{mar}} - \mu_i^p|$
21:   $\delta_{i,t,d} \leftarrow \min\{\delta_{i,t,d-1} - \mu_i^p, 0\}$
22: else if $\delta_{i,t,d} > 0$
23:   $\delta_{i,t,d} \leftarrow \max\{\delta_{i,t,d} - \gamma_i^c, 0\}$
24: else
25:   $\delta_{i,t,d} \leftarrow \min\{\delta_{i,t,d-1} - \mu_i^p, 0\}$
26: else
27:   $\delta_{i,t,d} \leftarrow \min\{\delta_{i,t,d-1} - \mu_i^p, 0\}$
28: else
29: end if
30: else
31: $\delta_{i,t,d} \leftarrow \min\{\delta_{i,t,d-1} - \mu_i^p, 0\}$
32: else
33: end if
34: else
35: $\delta_{i,t,d} \leftarrow 0$

The sell and buy arbitrage flags are $u^a$ and $d^a$ respectively. They are initialized to be False and depending on whether they satisfy the conditions mentioned in Algorithm 2, they are set to be True or remain False.

Steps 5 to 8 in Algorithm 2 govern the imbalance calculations of the storage agent when the energy constraints are activated but the charging and discharging rate constraints are not activated. Steps 5 and 7 would govern a selling and buying behavior respectively. Equations (3) and (4) are used to determine the volume decisions of the storage in this time duration. Steps 12 to 35 in the same algorithm denote the behavior of the energy storage when the ramping constraints are activated. During this time the volume decisions are given by Equations (8) and (9):

\[
\begin{align*}
\hat{\pi}_{i,t,d}^a &= \begin{cases} 
0, & \text{if } d^a = \text{False} \\
\min\{p_{i,t,d}^{\text{mar}} - \min\{C_i, 0\}, \gamma_i^R \cdot r_i^{dch}\}, & \text{else}
\end{cases} \\
\hat{\pi}_{i,t,d}^{dch} &= \begin{cases} 
0, & \text{if } u^a = \text{False} \\
\min\{p_{i,t,d}^{\text{mar}} - C_i, \gamma_i^R \cdot r_i^{dch}\}, & \text{else}
\end{cases}
\end{align*}
\]

V. CASE STUDIES

In this section, we discuss the case studies performed to demonstrate the functioning of the proposed ABM. The simulations are carried out in Python 3.8 with an Intel(R) Core(TM) i7-10850H CPU @ 2.70 GHz machines. All the codes and data used for the simulations are available at [14].

The case studies consider four trading agents, one of each type, wind, consumer, thermal, and energy storage agents, and one market operator agent who is responsible for managing the CID market. All the trading agents adopt naive strategy for deciding their orders. Based on the evolution of the transaction prices and the updated limit prices, it is determined which agents get cleared in the CID market. From the moment of gate-opening (GO) of the CID market, if the transaction prices are above the limit to sell prices of storage and/or thermal agents then they tend to sell. In the due course of time, the transaction price goes on reducing then a point will be reached where the battery and/or thermal agents can start buying.

Fig. 3(a) and Fig. 3(b) demonstrate the volume traded in CJD market for different DPs by the storage agent for switch parameter set at 30% and 80% of the trading timeline respectively. In Fig. 3(a), as the switch parameter is shifted towards the GO time as compared to Fig 3(b). As a result of the energy constraints and charging rate constraints, the battery agent starts buying back quite early in the trading horizon for each corresponding DP. However, during this time, the transaction prices are also higher, which leads to the battery paying a higher cost in the transactions. Comparatively, in Fig. 3(b), the battery agent buys towards the end of the trading horizon which observes a lower transaction price.

For the thermal agent activating ramping constraints at an earlier time instant, for example, at 30% of the timeline for each DP, as shown in Fig. 4(a) results in thermal agent selling more around the respective switch instances. However, for the other case, when the switch takes place at 80% of the trading horizon as shown in Fig. 4(b), the agent does not sell more. It instead enters the real-time with an imbalance where it gets paid at a higher price, considering that the system is in energy deficit.

VI. CONCLUSION

In this work, we present an extended agent-based model to simulate the trading behavior of renewable, consumer, thermal, and storage agents for all the delivery products in the continuous intraday (CID) market which is operated by a market operator agent. To simulate a realistic trading behavior, a user-defined parameter, switch, is introduced for the storage and thermal agents to allow them to choose the time-instant in
the trading timeline when the traders can switch from trading towards increasing their profits to considering their physical constraints in the CID market. The different choices of switch parameter of the agents were found to affect their trading behavior thereby impacting their revenues earned or costs paid. The estimates of imbalance prices are instrumental in deciding the limit prices of the agents which affect their traded volumes. This coupled with the choice of switch parameters influences the imbalances created by the agents at the end of the CID market. If the system provides a correct price signal to the agents, the imbalances created by the agents at the end of the CID market will help the system to balance in real-time, and also the agents can earn higher revenues.

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