Comparative Techno-Economic Analysis of Market Models for Peer-to-Peer Energy Trading on a Distributed Platform

Marco Galici[a,*], Matteo Troncia[a], Morsy Nour[a,c], José Pablo Chaves-Ávila[a], Fabrizio Pilo[b]

[a] *Institute for Research in Technology (IIT), ICAI School of Engineering, Comillas Pontifical University, Madrid, Spain*
[b]*Department of Electrical and Electronic Engineering, University of Cagliari, Cagliari 09123, Italy*
[c]*Department of Electrical Engineering, Faculty of Energy Engineering, Aswan University, Aswan, Egypt*

Abstract

Since the emergence of distributed energy resources, local electricity markets have garnered interest for energy sharing on a community scale through both centralized and distributed models, including innovative distributed platforms. Numerous studies and initiatives have demonstrated that local markets and peer-to-peer transactions can be effective for electricity networks under specific conditions. Amidst the growing exploration of local market models, there is a noticeable gap in quantitative techno-economic analyses comparing different auction mechanisms. This paper aims at filling this gap by representing a comparative analysis of the most commonly implemented double-sided market models for peer-to-peer transactions based on a distributed ledger implementation. The comparison is based on quantitative key performance indicators designed to assess the economic and technical performance of these market models, including technical constraints within the power system through a network constraints management market. According to the selected metrics, the simulation results reveal that no single model outperforms all others. The authors conclude that, under the tested application and assumed conditions, the distributed market using distributed ledger technology faces several challenges that hinder its efficient application to local energy trading.

Keywords: peer-to-peer energy trading; local electricity markets; techno-economic analysis; double auction models comparison

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Nomenclature

RES	Renewable Energy Source
DER	Distributed Energy Resource
EV	Electric Vehicle
EC	Energy Community
VPP	Virtual Power Plant
LEM	Local Electricity Market
TSO	Transmission System Operator
DSO	Distribution System Operator
IMO	Independent Market Operator
DLT	Distributed Ledger Technology
P2P	Peer-to-Peer
DA	Double Auction
CDA	Continuous Double Auction
PCDA	Pseudo-Continuous Double Auction
MCP	Market Clearing Price
CMM	Constraints Management Market
PTDF	Power Transfer Distribution Factor
FSP	Flexibility Service Provider
EVM	Ethereum Virtual Machine
KPI	Key Performance Indicator
LW	Local Welfare
CQR	Clear Quantity Ratio
WCT	Waiting Clearing Time
CPX	Algorithmic Complexity
GC	Gas Cost
FC	Flexibility Costs
FV	Flexibility Volume
PV	Photovoltaic
CHP	Combined Heat and Power
CS	Charging Station
ZI	Zero Intelligence

1 Introduction

Global electricity generation from renewable energy sources (RESs) is swiftly rising in response to environmental concerns, economic factors, and energy security objectives [1]. A considerable percentage of RES generation is produced by small generating units connected to the distribution network (i.e., distributed energy resources (DERs) like electric vehicles (EVs), energy storage, flexible loads, etc.) [2]. The ongoing energy transition trends can be summarized in the concepts of decarbonization, decentralization, digitalization and democratization [3]. These trends influence the transformation of the energy sector, each addressing different dimensions of the shift towards more sustainable, efficient and user-centered energy systems.

Decarbonisation involves the transition to low-carbon or carbon-neutral sources [4]; decentralization in the energy sector refers to the shift from large, centralized energy production facilities to smaller, geographically distributed systems close to where energy is consumed [5]. Energy digitalization is the integration of digital technologies into energy systems to make them smarter, more efficient and more reliable [6]. The concept of democratization refers to the process of making energy systems more accessible, inclusive and participatory [3]. This involves shifting control and decision-making power from centralized entities and large corporations to local communities, individual consumers and smaller-scale producers. Democratization allows a broader base of stakeholders to influence how energy is produced, distributed and consumed, fostering greater community engagement, ownership and responsibility over local energy resources. Energy communities (ECs) are key for the democratization of the energy sector. They represent groups of citizens, local authorities, small businesses and cooperatives that collaboratively produce, consume, manage and share energy, often through renewable sources [7]. Microgrids and virtual power plants (VPPs) have been proposed to aggregate and manage energy communities' DERs fostering power system integration and system services provision [8]. Moreover, local electricity markets (LEMs) represent a forward-looking strategy for ECs [9]. The LEM for energy trading allows active customers to trade energy surplus directly with their neighbors [10], [11]. LEM deployment can support goals such as increasing local self-consumption, achieving supply-demand balance at the local level, postponing and reducing grid investments, and maximizing economic benefits for LEM participants [12]. Furthermore, LEM may support distribution system congestion management and, through ad-hoc TSO-DSO coordination, at the transmission level [13].

LEM deployments vary based on the adopted model: centralized or distributed. In a centralized model, a LEM could be operated by a central entity such as an independent market operator (IMO), distribution system operator (DSO), retailer, aggregator, or similar. Alternatively, in a distributed model, a LEM operates without the need for a central entity to run the market, hence clear the market and define the transactions among the peers [14]. The literature offers different designs of distributed market models and implementations concerning the theoretical and mathematical aspects of LEM design [15]. However, for a real scale LEM development, implementation aspects related to policy-making and regulation, grid operation and management, digital technologies, and transitional and integration aspects have to be considered, in the same way as highlighted in [16] for wholesale electricity markets and in [17], [18] flexibility acquisition mechanisms. Considering the context characteristics, a tradeoff among the different implementation aspects may lead to the implementation of a market design that is, in theory, economically less efficient but easier to implement [19].

Considering the digital technology implementation aspects for LEMs, the literature includes proposals for distributed market platforms utilizing ICT and distributed ledger technologies (DLTs) technologies (e.g., blockchain platforms and cryptocurrencies) [20], [21]. DLT refers to a broad category of technologies that distribute data across multiple nodes, blockchain technology is a specific type of DLT characterized by its chain of blocks [22]. The P2P trading for LEM and blockchain concepts are well-matched; The most significant features of a such platform are, *i*) programmability/automation (i.e., adaptability to a new set of instructions), *ii*) decentralization (i.e., transfer the management of certain operations to several entities), and *iii*) cyber-security (i.e., resistant to cyber-attacks); the literature has extensively explored this combination [23]. In particular, when it comes to P2P transactions, many articles rely on blockchain-based local P2P auction markets [24].

As an alternative to centralized LEM, distributed LEM models could solve issues such as single point of failure, privacy concerns, and scalability issues, as highlighted in the literature where different LEM models are proposed. In [25], the authors describe the market models suited for LEMs in four main groups: optimization and operations research methods, game theoretic methods, heuristic methods and finally data-driven methods. The first group concerns lagrangian decomposition problems, like social welfare maximization, while the game theoretic methods group describes the dynamics of participants' interaction in games. The heuristic group describes problem-solving methods that use practical techniques to find solutions. Finally, the last group encompasses various methods, like statistical and machine learning techniques. Here, in this paper the first group has been selected through a social welfare maximization using different double-sided auction methods. The concept of a P2P auction market for ECs is proposed considering various models; advocating for further studies that demonstrate which market model is the most effective and efficient for the considering context. A review of the literature that proposes and assesses LEM for P2P energy trading based on decentralized models is provided. Many articles rely on blockchain to build the P2P market model; moreover, it is found that several articles depend on qualitative indicators or utilize an insufficient number of quantitative metrics to ascertain the superiority of a particular market model. For instance, [26] compared a distributed LEM implemented on distributed platform and a centralized LEM implemented on a central structured query language database considering computation time. The study found that distributed LEM requires a much larger computation time than central LEM. However, considering the computational time metric only may not be sufficient to decide on the technical superiority of a LEM implementation. In [27], the authors aim to enhance the anonymity and security of transactions by implementing P2P transactions in a DLT platform using a decentralized flocking-based double auction market model. The paper presents a comparison in terms of traded volumes and convergence times of auction models developed in different distributed and centralized platforms. However, no economic indicators are proposed, limiting the evaluation. In addition, the only market phase implemented involving the distributed platform is the measurement phase. Therefore, the comparison is not between centralized and decentralized models but between centralized models and hybrid models that consider two criteria (economic and security of transactions). In [28], the authors compare different double auction models (a k-double auction model to allow users to decide on the transaction's final price, a uniform double auction in which the final price is set to be the intersection point between aggregated supply and demand curves, and a discriminatory double auction also called pay-as-bid) in terms of revenue and expenses; however, these metrics are limited to economic metrics, while technical market indicators are not discussed. In [29], a trading system based on blockchain technology and game theory is proposed and assessed. Specifically, energy transactions occur according to a double auction market model implemented through a modified version of the Vickrey auction. The paper compares three market models in terms of energy volume and convergence time of the distributed platform highlighting how suitable the proposed model is for its distributed implementation. However, the comparison remains limited to metrics focused only on blockchain technical aspects, lacking a quantitative assessment of the economic performance of the market model. In [30] the authors propose and assess a P2P energy trading model based on an iterative double auction market and blockchain. However, market performance assessment is presented only in economic terms. In [31], the authors propose an open-source framework released to test and simulate different microgrid configurations operated under a P2P approach based on auction-based market. The study focuses on the development of different phases of the double auction market on blockchain. Network constraints are not considered, and the analysis is limited to the economic performance of the single double auction model, neglecting the technical performances of the distributed platform. Many studies focus on either the economic or technical aspects when evaluating the market models and platforms adopted. However, the technical assessments are often limited to metrics such as convergence or computational time. Some papers go further by evaluating the technical aspects in terms of the operational costs associated with using the platform. For instance, a comparison of auction-based P2P trading is provided in [32], where the authors analyze computational time and computational costs, called in the study market complexity, in an auction-based P2P context. However, in the study an economic metric is missing. In [33], the authors extend the analysis by including not only economic metrics, but also indicators of network constraints and different pricing market mechanism designs, such as static limits, dynamic operational envelopes and distribution locational marginal pricing, highlighting the impact on market costs and regulatory aspects. In this study, however, the technical evaluation appears to be limited to the evaluation of market and platform costs, without a study of computational time. The authors in [34] present an evaluation of auction-based P2P markets, similarly focusing on economic metrics and computation time, but with a limited focus on the market costs and computational burden. In contrast, [35] discusses computational time and burden of the market and platform but omits economic metrics, providing an in-depth look at the trade-offs between efficiency and feasibility in auction-based LEM implementations. Similarly, an analysis of the decentralized market model can be found in [36], where the focus remains on economic and market complexity aspects, but does not extend to computation time. Regarding the use of blockchain technologies, in [37] the potential of a blockchain-enabled P2P trading in terms of market complexity and computation time is analyzed, showing that while blockchain increases security and transparency, it also introduces significant computational burden.

Moreover, another aspect of market design concerns the market phases that characterize each market implementation, that go from procurement to settlement [38]. In principle, DLT can be exploited in several market phases, however, in the literature, DLT platforms are limited to the distributed database features for measurement or settlement, with no exploitation of its functionality for other market operations such as bid collection, market clearing and quantification of the cleared quantities. For instance, [39] adopts blockchain technology only for the measurement phase in a distributed P2P energy trading developed for a residential community in Amsterdam, the Netherlands. The community contains PV, energy storage, and EVs operating in charging mode. The study found that P2P trading reduces the energy exchange with the grid for all LEM participants and the energy costs. In [40], a distributed solution for auctions is introduced and validated through testing under different scenarios, and a comprehensive cost and security analysis is provided. The study employs the blockchain only as a tracker of bids and as a distributed storage system to upload bidding-related documents. Furthermore, in [41], an electric vehicle trading system based on blockchain is adopted only for the measurement and settlement market phase. Blockchain is used to record transactions to increase market platform security. To determine prices, game theory through Bayesian gaming is included in the model to define an auction-based market. For instance, in [42], a distributed trading mechanism for local markets is proposed. The results propose a comparison in economic terms of the different auction-based discrete market models with blockchain used only for the measurement phase. In [43], the study proposes a market mechanism based on game theory, in which retailers and prosumers negotiate iteratively to maximize their profit. The negotiation and clearing mechanism, implemented as smart contracts on the blockchain, is based on the best price principle. Users submit their offers, and when a better offer comes in, it replaces the previous one. However, the paper considers only a simplified double auction market model. The blockchain is exploited for the clearing process, but its effectiveness is neglected in the results that focus only on the economic relevance of the model.

Besides academic advancements, many pilot projects and startups developed decentralized LEMs. For instance, the Brooklyn microgrid project developed by LO3 energy company was the first to implement a decentralized auction market for a community neighbor in New York, USA, where blockchain was limited to providing a secure environment for storing market data. After that, many other projects were implemented in different countries. In the Quartierstrom project in Switzerland [44], a private blockchain-based double auction market was implemented in a community containing 37 houses. The houses have DERs, such as PV, ESS, and EVs. Additionally, each house is connected to a smart meter linked with the distributed platform. In this way, the platform can manage the measurement and the settlement phases. The project aims to test the decentralized LEM technically and check the market participants' behavior [45]. For clarification, Table 1 summarizes the articles in the literature review according to the metrics considered, the market models used and the adoption of network constraints.

Table 1. Literature review summary.

	Metrics Considered						
Ref	**Economic Metrics**	**Transaction Volumes**	**Computational Times**	**Complexity of the Markets**	**Network Constraints Metrics**	**Market Model**	**Network Constraints**
[26]			✓			Centralized and Decentralized Double Auction	No
[27]		✓	✓			Decentralized Double Auction	No
[28]	✓					Centralized and Decentralized Double Auction	No
[29]		✓	✓			Decentralized Double Auction	No
[30]	✓					Iterative Double Auction	No
[31]	✓	✓				Auction-based P2P	No
[32]			✓	✓		Auction-based P2P	No
[33]	✓			✓	✓	Decentralized Pricing Design	Yes
[34]	✓		✓	✓		Auction-based P2P	No
[35]			✓	✓		Auction-based	No
[36]	✓			✓		Decentralized Auction	No
[37]			✓	✓		Decentralized P2P	No
[39]	✓					Auction-based P2P	Yes
[40]	✓					Decentralized Auction	Yes
[41]	✓					Auction-based	No
[42]	✓					Auction-based	No
[43]	✓					Game-theory Auction-based	No
[44]	✓	✓			✓	Decentralized P2P	Yes
[45]		✓			✓	Decentralized Auction	Yes
This work	✓	✓	✓	✓	✓	Centralized and Decentralized Double Auction	Yes

In light of this analysis, this study wants to broaden the tools available for decision-making processes involved in the development and evaluation of market platforms that adopt ICT and decentralization and digitization technologies. This involves a comprehensive techno-economic assessment that goes beyond limited technical metrics (such as convergence and computing time) and incorporates assessments of network constraints, market complexity in terms of cost and computational burden, and the overall cost-benefit ratio of different platform models and architectures. To address the existing gaps, the study proposes assessing market models for LEMs based on a blockchain technology implementation as a distributed platform, where the technology is employed for different market phases (i.e., managing and storing user and market data and market clearing). The contributions of this paper are as follows:

- Quantitative comparative performance evaluation of different market models for LEMs based on discrete and continuous double auctions. The comparison is addressed by considering a distributed implementation for the LEMs models. The techno-economic assessment is based on economic indicators, market complexity (computational time and burden), and network constraints management effectiveness. The analysis is based on a study considering a realistic representation of an Italian distribution network.
- Examination of distributed technologies for numerous market operations such as bid collection, market clearing and quantification of cleared quantities.
- Implementation of a P2P energy trading model considering three double-sided market designs (i.e., double auction (DA), continuous double auction (CDA), and pseudo-continuous double auction (PCDA)) adopting a DLT as market platforms, in which the evaluation of network constraints is present.

The paper is organized as follows. Section 2 presents the auction market models. Section 3 briefly describes the blockchain technology and the distributed market implementation. In addition, it contains the market's agent behaviors and reports the KPIs to evaluate the market models. Finally, Section 4 presents the case study for LEM evaluation and the results with discussions. Section 5 concludes the study.

2 Generalized algorithm for the market models under analysis

Centralized market models consider that the market is entrusted to a third-party entity (i.e., the MO) to ensure the market functioning. The MO collects bids, manages the clearing process, and redistributes the expenses and revenues established in the market. Distributed markets are characterized by no central entity with the MO role, they can be managed by an inherently distributed platform and exploit distributed algorithms or game theory to address the market functioning, resource allocation occurs in a decentralized manner. This paper provides the techno-economic assessment of three LEM models through their implementation: the double auction (DA) [46], the pseudo-continuous double auction (PCDA), and the continuous double auction (CDA) [47]. In the study, all the market models are implemented as a prototype of a DLT platform realized through blockchain technology with smart contract functionality. Fig. 1 depicts the generalized algorithm for the proposed market models. The differences between the three market models and their implementations proposed in this paper are discussed in detail in this section.

In this paper, the DA market model is implemented with a pay-as-clear clearing mechanism that generates peer-to-MO smart contracts; whereas, in the PCDA, and CDA auction markets are distributed market model that define P2P smart contracts.

The DA, CDA, and PCDA models considered in this paper for a local energy market are based on three main processes:

- *The energy trading process* defines the bidding and clearing rules (section 2.1).
- *The congestion and voltage check and management process* verify the compliance of network constraints after each trading period. It allows the network operator to procure bids to avoid congestion and over/under-voltage (section 2.2).

These two processes collectively form the framework for the three market models. In this paper, the market models are designed considering that each offer is an elastic limit order, which implies that the constraint price expresses the willingness to sell (or buy) the energy not exceeding the specified amount at a price, not less (or more) than that specified in the bid. In addition, it is assumed that the energy sold by the retailer external to the LEM is higher than the energy selling prices of LEM participants. The energy retailer is designated as the last buyer/seller for ECs users to prevent any actors from being left without service due to an inability to access the market.

2.1 Energy trading period

This section describes the energy trading period characterized by the trading mechanism protocol (i.e., the rules that define the exchange process between buyers and sellers in the market) for the DA, CDA, and PCDA models considered for the techno-economic assessment. The energy trading period is divided into two stages: *i*) the bid presentation stage and *ii*) the market clearing stage. The first stage is the same for the three market models considered, the second stage differs depending on the market model.

2.1.1 Bid presentation stage

In the three market models considered, multiple buyers and sellers compete by submitting two types of bids: *i*) bid to buy and *ii*) bid to sell. The bids consist of energy quantity, energy price, identification number, and connection node identifier. Both bids are considered orders to buy or sell with a price constraint. Information about the state of the market is made public to all market participants through the order books, where bids to buy and to sell are sorted according to the price in descending order and ascending order, respectively.

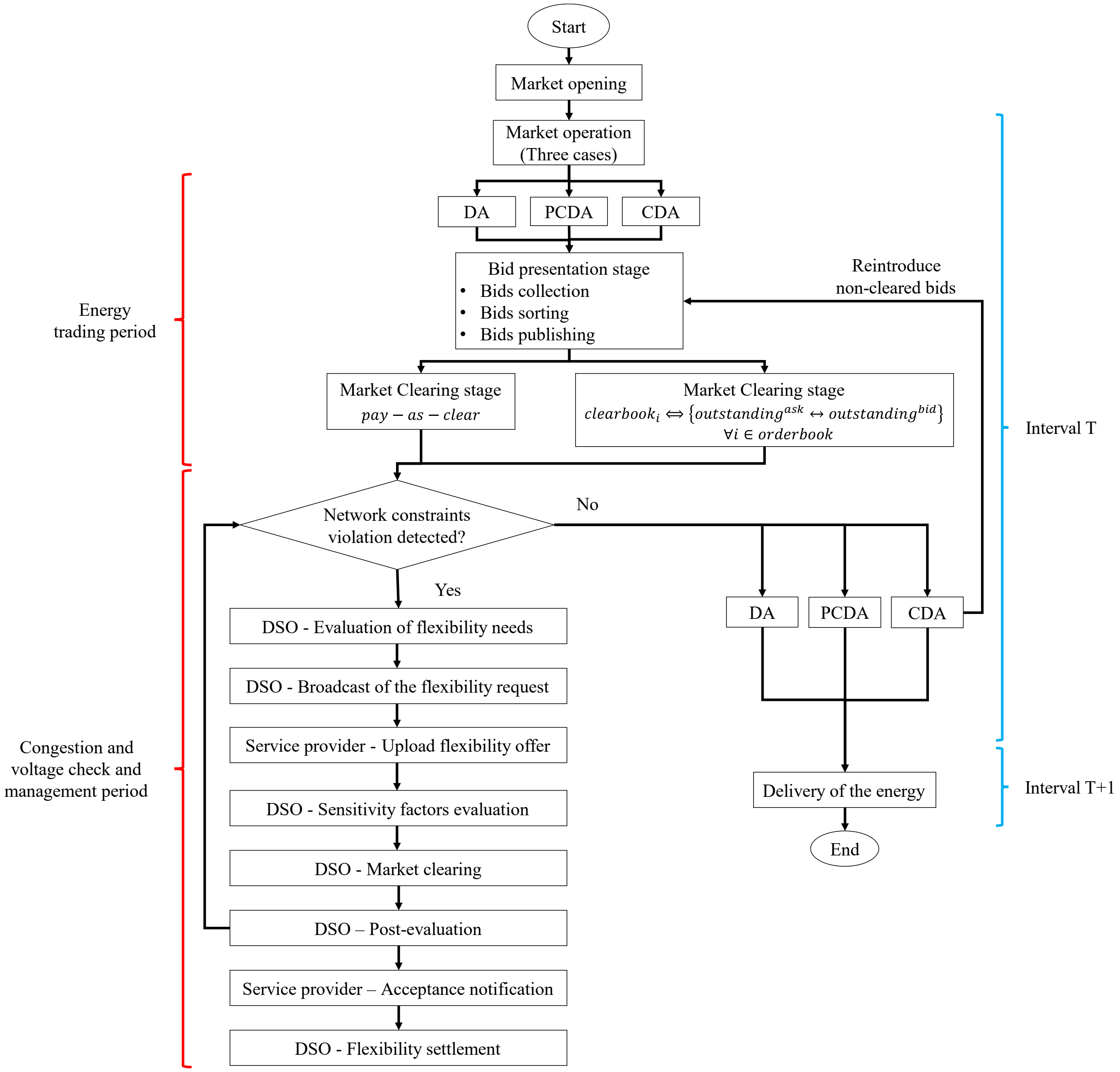

Fig. 1. The flowchart of the generalized algorithm proposed for the market models under analysis: double auction (DA), pseudo-continuous double auction (PCDA), and continuous double auction (CDA).

2.1.2 Market clearing stage

This section describes the market clearing stage that concerns the bids matching mechanism. The three market models implemented in this paper (i.e., DA, CDA; and PCDA) are based on different algorithms for the LEM bid-matching process. It should be noted that the algorithms presented are logic flows that describe how the process of matching bids takes place for each model. Consequently, they are executed in a single step to determine the output (price and quantity pairs) based on the input data.

Table 3.1 presents the market clearing algorithms for the DA model (Algorithm 1) and the CDA and PCDA models (Algorithm 2). Table 2 reports the definition of the quantity used in Algorithms 1, 2, and 3. In Algorithms 1 and 2, the input parameters are the price and quantity pairs for the supply and demand curves; the output is the price and the quantity pairs that clear the market. In those algorithms, the $match_{Energy\ Retailer}$ function describes how the remaining bids in the order books match the energy retailer prices, which algorithm is presented in Table 3.2 (Algorithm 3). For all market models, this function is executed every time the clearing process occurs, just before the congestion and voltage check and management period.

As depicted in Fig. 1, the clearing of the DA market implemented requires the MO to collect and sort all bids; then determines the market quantity, clearing price, the accepted bids, and the injection and withdrawal schedules, as defined in [46]. The equilibrium price is unique and equal to the Market Clearing Price (MCP).

Table 2. Algorithm's nomenclature.

Name	Description
p	Price term
q	Quantity term
i	Demand index
j	Supply index
$supply^{p,q}$	Supply bid in terms of price and quantity
$demand^{p,q}$	Demand in terms of price and quantity
$obook_{buy}^{p,q}$; $book_{buy}^{p,q}$	Orderbook of the buy orders in terms of price and quantity
$obook_{sell}^{p,q}$; $book_{sell}^{p,q}$	Orderbook of the sell orders in terms of price and quantity
$cbook^{p,q}$	Book of the order matched in terms of price and quantity

The distributed implementation of the LEM models developed in this paper share some common features, each characterized by structural differences. In PCDA, the arrival time of the bids is not considered during the matching mechanism. Unlike CDA, in which the market is cleared continuously, in the PCDA market, the clearing process is performed only once. Hence, considering the temporal dimension, this market mechanism is intermediate between DA and CDA. Since there is no central entity, the bids' collection process is entrusted to the distributed platform entity. Once the bid presentation stage is completed, the distributed entity will sort the bids by creating the order books for purchasing and selling bids according to the "price" field. The highest quote of a buyer is called the outstanding bid, and the lowest quote of a seller is called the outstanding ask to identify the suitable bids to be coupled [48].

During the matching process, the outstanding bid is matched with the outstanding ask, and the transaction price is the average of their quotes. This matching process continues until the outstanding bid is lower than the outstanding ask - or when there are no bids or asks in the market. The matching process involves matching the purchasing offer with the highest price and the selling offer with the lowest price first. The trading price will equal half the prices offered for purchase and sale.

Table 3.1 - Market clearing algorithms for the DA model (Algorithm 1) and the CDA and PCDA models (Algorithm 2)

Algorithm 1 – DA clearing algorithm

Input $supply^{p,q}$, $demand^{p,q}$
Output p, q
$p, q, i, j = 0$
while $min\left\{\sum_i demand_i^q, \sum_j supply_j^q\right\} > 0$
  if $demand_i^p \geq supply_j^p$ **do**
    $p = min\left\{demand_i^p, supply_j^p\right\}$
    if $demand_i^q > supply_j^q$ **do**
      $q += supply_j^q$
      $demand_i^q -= supply_j^q$
      $supply_j^q = 0$
      $j += 1$
    else if $demand_i^q < supply_j^q$ **do**
      $q += demand_i^q$
      $supply_j^q -= demand_i^q$
      $demand_i^q = 0$
      $i += 1$
    else do
      $q += demand_i^q$
      $demand_i^q = 0$
      $supply_j^q = 0$
      $j += 1$
      $i += 1$
    end if
  else do
    $break$
  end if
end while

call function $match_{Energy\ Retailer}^{p,q}\left(supply^{p,q};\ demand^{p,q}\right)$

Algorithm 2 – CDA and PCDA clearing algorithm

Input $obook_{buy}^{p,q}$, $obook_{sell}^{p,q}$
Output $cbook^{p,q}$
for $\_k : min\left\{length\left(obook_{buy}\right); length\left(obook_{sell}\right)\right\}$
  if $obook_{buy,\ \_k}^{p} \geq obook_{sell,\ \_k}^{p}$ **do**
    $pr\_c = mean\left(obook_{buy,\ \_k}^{p,q}; obook_{sell,\ \_k}^{p,q}\right)$
    if $obook_{sell,\ \_k}^{q} \geq obook_{buy,\ \_k}^{q}$ **do**
      $cbook_{\_k}^{p,q} \leftarrow contract\left(pr_c;\ obook_{buy,\ \_k}^{p,q}\right)$
    else do
      $cbook_{\_k}^{p,q} \leftarrow contract\left(pr_c;\ obook_{sell,\ \_k}^{p,q}\right)$
    end if
  else do
    $break$
  end if
end for
call function $match_{Energy\ Retailer}^{p,q}\left(obook_{buy}^{p,q};\ obook_{sell}^{p,q}\right)$

Table 3.2 – Algorithm for the energy Retailer Matching process for unmatched bids (applies for DA, CDA, and PCDA)

Algorithm 3 – Energy Retailer Matching process for unmatched bids

Input $book_{buy}^{p,q}$, $book_{sell}^{p,q}$
Output $cbook^{p,q}$
for $\_bid : book_{buy}$ **and** $\_ask : book_{sell}$ **do**
  $cbook^{p,q} \leftarrow \begin{cases} contract\left(ER_{sell}^{price}, \_bid^q\right) \\ contract\left(ER_{buy}^{price}, \_ask^q\right) \end{cases}$
end for

2.2 Congestion and voltage check and management period

Grid congestion happens whenever the power flow through an element (e.g., line, transformer) determines overloading. In addition, high consumption or production can create voltage violation issues. Each exchange defined in the market complies with network constraints. In this paper, line loadings and node voltages are calculated using the power flow algorithm [49]. For the three market models, the power flow is centralized and performed by the DSO.

As depicted in Fig. 1, the congestion and voltage check happen once the cleared book is closed, showing how the purchasing and selling bids are matched, hence, no more energy transactions are allowed. If constraints are violated, network users' power injection and consumption must be changed to avoid the network constraints violations due to the electricity exchange established by the LEM results. In this paper, the DSO is in charge of avoiding network constraints violation, DSO is responsible for acquiring the necessary flexibility from market participants. Flexibility acquisition follows a different procedure for the three market models implemented (i.e., DA, CDA, PCDA). The constraint management in the form of flexibility market occurs only once after gate closure time for the DA and PCDA markets. In contrast, it may occur more than once for the CDA market because the flexibility market occurs whenever there are constraint violations after the energy trading period clearing, that performed continuously. The network constraint management period ends with a further network constraint check addressed by the DSO through a power flow calculation that considers the results of the flexibility market. The congestion and voltage check and management period entails a Constraints Management Market (CMM) operated by the DSO. The DSO acquires the necessary flexibility from the network customers belonging to the LEM to avoid the detected network constraint violations. The CMM is formed by nine steps addressed either by the DSO and the potential service providers.

1. *DSO Network constraints violation check from local electricity market results*. If the power flow reveals a network violation the DSO starts the remedial procedure through the CMM.
2. *DSO evaluates the flexibility needs*. The DSO calculates its flexibility needs (i.e., the amount of energy that the distributed resources must vary from their schedule) based on the power flow results. DSO flexibility needs are requests for active power in either an upward or downward direction.
3. *DSO Broadcast flexibility request*. The DSO transmits the flexibility request to the market platform, then all market participants can offer flexibility once the request is published on the market platform [50].
4. *Service providers' flexibility bid submission*. When the DSO uploads the flexibility request on the market platform, the CMM opens, eligible users can upload their flexibility offers in terms of price, maximum and minimum quantity, and connection node. Eligible users are market participants that were able to buy and/or sell energy during the energy trading period relevant for the CMM. This definition is of no interest to the DA and PCDA markets, as the congestion market opens once the energy market is closed for the trading period. However, this definition is relevant for the CDA market as the DSO can request flexibility from users several times during a single transaction period. Therefore, not all network users can participate in the CMM during a trading round.
5. *DSO Sensitivity factor evaluation*. The grid information is considered in the market clearing using linear network representation by adopting sensitivity factors. Thus, the DSO calculates the sensitivity factor for each flexibility provider depending on the locations of the constraint violation. In this paper, sensitivity is based on the matrix that represents in each element the sensitivity between the nodal voltage magnitude changes and the nodal active power injections (for voltage support procurement) [51] and the DC PTDF matrix (for congestion management) [49]. Although with AC PTDFs it is possible to discriminate among flexibility providers downstream of congestion, with DC PTDFs it is still possible to preserve the topological information about the network but with less precision in representing the magnitude of the impact of providers on the congestion. For this study, the DC PTDF provides a signal for service providers to participate in the market based on the congestion location.
6. *DSO Market-clearing*. In the market clearing process, the most effective bids from the flexibility providers are selected to solve the network violation at the minimum cost. The DSO gathers all the flexibility provider bids to perform the market clearing. Afterward, the DSO solves the market-clearing problem [52].
7. *DSO Post-evaluation*. Finally, the DSO performs a new power flow analysis based on the new resource profiles resulting after the market clearing to check network constraint violations.
8. *Service Providers acceptance notification*. If the DSO's post-evaluation is successful - after the market clearing step - users selected for their flexibility are notified.
9. *DSO Flexibility settlement calculation*. The flexibility payment is made through a redistribution of costs to LEM participants. The cost of managing the grid through flexibility requests is proportional to the energy each user trades in the energy market. This redistribution of costs implies that if a user does not buy (or sell) energy from (to) the grid, the user would have no additional cost to pay for the flexibility request, as the energy exchanged in the energy market would be zero. Equation (1) defines how the flexibility cost is distributed.

$$c_h^{CMM} = \frac{c_{CMM} \cdot kWh_h}{\sum_{i=1}^{N_{user}} kWh_i} \quad \forall h \in N_{user} \tag{1}$$

Where c_h^{CMM} is the proportional flexibility cost for user h, c_{CMM} is the total flexibility cost, and kWh_h is the energy exchanged by user h in the energy market.

3 Market Models Implementation and assessment framework

3.1 Architecture of the market platform for the distributed implementation of the three market models

A modern marketplace must be user-friendly and technologically advanced, with internet access for all users [53]. Typically, the energy market platforms consist of four fundamental elements: *i*) Data acquisition (i.e., reading consumption and production data), *ii*) Data management (i.e., user-market interactions), *iii*) Data processing (i.e., market actions validation), and *iv*) Data provisioning (i.e., availability of data) [54].

In this paper, for the sake of addressing the techno-economic assessment of different distributed LEM implementations, the platform architecture assumes an automated network customer participation in the LEM through software agents; Fig. 2 represents the architecture of the market platform developed in this paper for the distributed implementation of the market models. Following [55], smart meters are used for data acquisition, the agent software module handles the management of actions such as sending buy or sell orders based on acquired data. Once the energy trading period ends, the market is ready to execute the clearing process through a dedicated module. Market clearing defines the pairs among the users' portfolios to ensure that money can be exchanged with the peers as a consequence of the energy trading.

The distributed market platform is based on four main functions: “Register participant”, “Place bid”, “Clearing market” and “Transfer money”. Each participant is assumed to be equipped with a smart meter to ensure the connection of each market participant to the market platform. Each smart meter has built-in functions, like the “Place Bid” or the “Register Participant” function, that allow each actor to interact with the market platform.

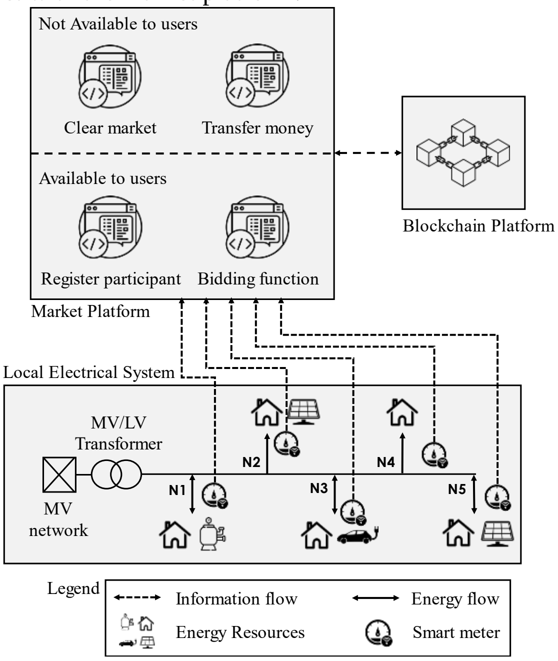

Fig. 2. Architecture of the distributed market platform implementation.

In this paper, the Ethereum blockchain is adopted for developing the distributed market model implementations. It represents an off-the-shelf DLT technology characterised by programmability for process automatization and self-executable programs (smart-contracts) features [56]. The Ethereum blockchain-based platform developed in this study ensures that market participants can publish their bids and clear up the market after the bids have been matched. In the following, some elements of the Ethereum blockchain are described due to their implication for the assessment of the distributed market models implementation. It must be highlighted that the proposed distributed market model implementation can be implemented in every DLT platform with programmability and smart-contract features. Without loss of generality, the proposed approach for market models’ comparative assessment should be adapted to consider the peculiarities of the adopted DLT platform.

Ethereum is a distributed computer that runs via a virtual state machine model called the Ethereum Virtual Machine (EVM). To encourage computation, Ethereum adopts an intrinsic currency called Ether. The smallest part of an Ether is called Wei and corresponds to 10^{-18} Ether. The computations on the EVM are limited by a parameter called gas. Tariffs for gas are applied in three distinct circumstances as a prerequisite for executing an action on the blockchain platform. The first situation occurs in the case of operation calculation [56]. The second case happens when a function is called or a smart contract is created. The last scenario occurs when volatile or non-volatile memory (i.e., increasing the required memory space) is used. The EVM is a stack-based machine whose main activity is moving temporary instructions to and from a push-down stack [56]. Each time an operation is performed, an instruction is added and removed from the stack; the number of instructions added and removed are represented by the parameters ($\boldsymbol{\delta}$) and ($\boldsymbol{\alpha}$), respectively, measuring algorithmic complexity. Furthermore, each time an instruction is added or removed from the stack, a cost function evaluates the entire cost, expressed as gas, required to execute the given operation (i.e., calculation, smart contract creation or usage of memory). Once the gas cost of an operation is evaluated, the user must send a transaction that covers the cost of that operation to insert it into the blockchain network permanently. This operation will be added to the blocks that constitute the blockchain. However, an additional fee must be paid to network miners that run the algorithm, the higher the fee, the faster the operation is validated and officially added to the blockchain network [57]. The final cost function in euros of a blockchain operation is represented by equation (8).

$$C_{€} = G \cdot F \cdot H_{€} \qquad (8)$$

Where $C_{€}$ represents the final cost in Euros, where G represents the cost in gas of the operation evaluated by the cost function that considers the stack parameters $\boldsymbol{\delta}$ and $\boldsymbol{\alpha}$, expressed by Gas; F represents the fee to the miners, expressed by GWei/Gas and $H_{€}$ represents the conversion factor from Ether to Euros. This factor enormously influences the cryptocurrency market [58]. The F parameters are highly volatile, but conversely, this depends on the miners and network actors, which are influenced by actions outside the blockchain.

3.2 Assessment framework for comparing the effectiveness of the market models implemented

One of this paper's objectives consists in addressing the techno-economic assessment of different market models for LEM considering their distributed implementation. The assessment framework is formed by the set of KPIs as defined in Table 5. These KPIs are selected to capture cardinal dimensions of market performance, from economic efficiency to technical and digital performance. Importantly, the lasts two indicators in Table 5are evaluated only for the scenario in which network constraint violations are detected. The KPIs presented in Table 5 shape the framework for assessing LEM market performance from multiple perspectives: economic, technical and digital point of view. While Local Welfare (LW), Cleared Quantity Ratio (CQR) and Waiting Clearing Time (WCT) capture the efficiency and liquidity of the market from an economic and technical point of view, as previous authors did [31], Algorithmic Complexity (CPX) and Gas Cost (GC) reflect the operational feasibility of the adopted distributed platform. These parameters only represent the complexity associated with the platform in the form of the number of processes required (such as saving data, sending data between users and memory usage of the platform) and platform cost [34]. Flexibility costs (FC) and flexibility volume (FV) highlight the importance of balancing network stability with market operations. Each indicator has a distinct purpose, providing a comprehensive point of view of market performance and enabling a robust techno-economic assessment of LEM implementation.

Table5 – Assessment framework with KPI description for LEM implementation assessment

Category	KPI	Description
Economic	Local Welfare (LW)	Net sum of consumer and producer surplus for LEM participants. The definition resembles social welfare [46], but "Local Welfare" indicates only the LEM participants' welfare. The higher the value of the LW metric, the better the social welfare of LEM users, the better the market implementation performance.
Technical-Market	Cleared Quantity Ratio (CQR)	How much energy is traded through a market model as a percentage of the total quantity offered for selling, defined as the ration of the total energy cleared and the total energy offered. The higher CQR, the higher the trading volumes and, thus, the greater market liquidity, the better the market implementation performance.
Technical-Market	Waiting Clearing Time (WCT)	WCT assesses how long it takes for an offer to be cleared by the market. This metric is calculated as the difference between the bids clearing time and a bid arrival time. The evaluation is based on the analysis of the time distribution performed on repeated simulations. The parameters adopted are the first quartile, the median, the third quartile, the minimum, and the maximum value, and the errors from the median value. The higher the WCT, the worse the market implementation performance.
Digitalisation	Algorithmic Complexity (CPX)	Distributed complexity is measured considering the complexity and corresponding execution cost of smart contracts on blockchain. In this study, the concept of complexity is linked to the blockchain platform, so the market complexity is determined by the number of operations required to execute a process in the blockchain platform. This metric is evaluated as the sum of ($\boldsymbol{\alpha}$) and ($\boldsymbol{\delta}$). The higher the CPX value, the greater the complexity, the worse the market implementation performance.
Digitalisation	Gas Cost (GC)	Cost of operating the market using the blockchain platform. This parameter represents the gas needed to execute a specific operation on the blockchain platform (the parameter G in (8)). The higher the GC value, the worse the market implementation performance.
Technical-Electrical	Flexibility Costs (FC)	FC assesses the total cost of the flexibility provided to the DSO, which is redistributed to market participants according to equation (1). The higher the FC, the worse the market implementation performance.
Technical-Electrical	Flexibility Volume (FV)	FV measures the amount of flexibility provided to the DSO, calculated as output of the CMM as the sum in absolute terms of the cleared flexibility for each SP. The higher the FV, the worse the market implementation performance.

4 Case study, results, and discussion

4.1 Case study

The case study concerns a realistic distribution grid scenario by exploiting a portion of a network from the ATLANTIDE database [59]. The grid portion is a rural distribution grid, radially operated representative of a three-phase, 4-wire, low-voltage (230/400 V) distribution network. The grid is fed by a secondary substation with a 250 kVA (20/0.4 kV) transformer. This node is selected as the slack bus. In the network, some peers present local generation for self-consumption, energy exchange, and charging the local battery (if present) or the available electric vehicle (if present). The test case, shown in Fig. 3, is a network of 16 nodes with five distributed generators (i.e., PV and CHP), five ESSs, and six EVs. In each node, a network customer able to participate in the markets is connected.

EVs input data are the charging power of the charging station (CS) and the hourly profile in which EV batteries are stationary and charging at the CS. Given the plethora of existing electric vehicles and for a more extensive representation of the different types of electric vehicles, the energy capacity in each battery is selected by a Gaussian distribution. According to an analysis of electric vehicles in the current market [60], the mean value of the distribution is set equal to 57 kWh, and the standard deviation is equal to 15. This last value is 1/3 of the difference between the market's maximum electric vehicle capacity value and the average capacity value considered. EVs operate only in the charging mode. The EV chargers' power rating is 3 kW. The EVs are assumed to be connected for charging between hours 18 and 7. They are used for mobility between hours 8 and 17. Simultaneously, the high penetration of distributed generation into the grid can overload the lines, particularly during periods of high generation, which produces an inversion of the power flow. Four different types of customers are connected to the network. Their typical profiles are based on the daily curves of the ATLANTIDE project [59]. This study considers the residential, industrial, and commercial profiles. In the distribution network, 2 PV generators are installed. The remaining generators are CHP generators. In particular, these generators' profiles account for the thermal production of the peer to which they are connected. Indeed, the CHP generators are destined for heating, not electricity generation. For simplicity and without loss of generality, the paper does not consider uncertainties related to the load and generation profiles. The energy market's maximum and minimum price values are 0.400 €/kWh and 0.025 €/kWh, respectively. For LEM participants, selling and buying bidding prices are randomly generated using a normal distribution function within this interval. For the electricity retailer, these values represent the prices at which energy is purchased and sold by LEM participants. These parameter values are arbitrarily defined, based on the Italian feed-in tariffs for 2019 [61]; however, other values can be considered without loss of validity. The maximum and minimum price values for the CMM are equal to 0.4995 €/kWh and 0.1662 €/kWh, respectively. The flexibility market prices are extracted from PicloFlex website market concerning the CMM prices. These two values are defined as the market's maximum and minimum closing values on a typical day during the winter of 2023/2024.

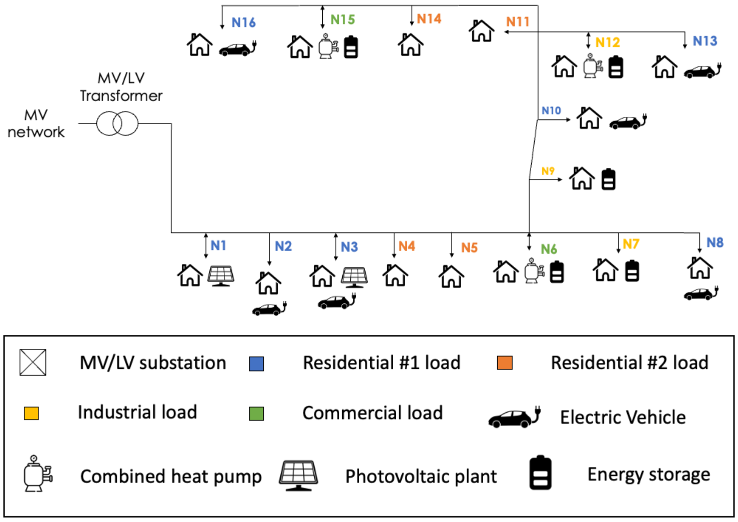

Fig. 3. Schematic diagram of the LV distribution network.

In a real market, the market actors should consider the offers from other participants to increase their profits. However, choosing a trading strategy is complicated as the different market models have distinct dynamic characteristics. Since the purpose of the study is not to produce trading strategies, the zero intelligence (ZI) strategy is easy to implement but ensures the user's profit [62]. ZI behavior involves random quotes in each range of Gaussian distribution without considering market transactions. The Gaussian distribution is truncated at a maximum and minimum value. The maximum and minimum values are the energy retailer's selling and buying energy prices. It is essential to mention that the ZI approach is applied not only to the energy market but also to the CMM. This means that users extract flexibility prices from a Gaussian distribution. The Gaussian distribution has a mean value equal to the average interval between retail and export prices. Instead, the standard deviation equals 1/3 of the gap between the retail price and the mean value.

The comparative analysis of the market models is conducted by exploiting two scenarios. Scenario A assumes that the portion of the network adopted as a case study does not have network congestion during the entire study interval. In contrast, scenario B includes network congestions that may occur in specific time intervals. To create scenario B, the branches "11-12" and "12-13" have an ampacity reduced by 47% compared to scenario A, where branch "11-12" represents the connection between node 11 and node 12. The choice of this reduction, and therefore of the two specific lines in the case study, is due to the desire to perform a proof-of-concept study.

The distributed implementation of the different market models has been developed on a test network called Ganache CLI [63]. The hardware requirements for running a Ganache CLI are largely influenced by the software dependencies of the Ganache framework, which include Nodejs [64] and npm [65]. Since Nodejs runs efficiently on a wide range of operating systems, including Linux, Windows, and macOS, the hardware needed to support Ganache will depend significantly on the nature of the workload and the specific use case. In this case study, the Ganache CLI test network and the simulation have been run on a workstation with 16 GB ram, Intel Core i7-6920HQ and 1 TB SSD.

4.2 Results and discussion: Scenario A (no congestions)

The results are presented in Table 6 (scenario A) in terms of the KPIs defined in section 3.2. In the following, the evaluation is based on comparing the three market models using the DA model as a reference for calculating the percentage values for the economic and technical-market KPI categories. For the KPIs belonging to the digitalization category the reference considered is the distributed implementation of the DA market.

As shown in Table 4, the DA market ensures the highest LW, as expected from marginal economic principle of its clearing mechanism. The PCDA economic performance mirrors the DA. This fact reflects the characteristics of the two markets. The PCDA market has the same solution as the DA market since the bid arrival time is not considered in the clearing algorithm, the complete set of bids for the relevant trading period is considered in the sorting processes. In contrast, the CDA continuously clears the bids in each market clearing round as soon as the bids are collected, disregarding potential future transactions that could lead to a higher LW value. Consequently, the DA and PCDA can reach the optimal LW value by evaluating the complete set of bids for that day, despite the different clearing mechanisms adopted. The CDA market achieves the best performances considering the CQR and WCT metrics.

Table 6. Comprehensive results (Scenario A).

KPIs		DA	CDA	PCDA
LW	Local Welfare [EUR]	24.204	23.599 (-2.50%)	24.204 (0%)
CQR	Clear Quantity Ratio [%]	24.933	27.452 (+10.10%)	24.933 (0%)
WCT	Waiting Clearing Time [min]	30.034	28.061 (-6.57%)	30.398 (+1.21%)
CPX	Complexity [$\boldsymbol{\delta}+\boldsymbol{\alpha}$]	8471	8878 (+4.80%)	5863 (-30.79%)
GC	Gas Cost [Gas]	995585	1017130 (+2.16%)	921378 (-7.45%)

On the other hand, the CDA market is the worst in terms of costs related to DLT and its complexity. This aspect is dictated by continuous matching, which increases user-ledger interactions considerably. The PCDA case is the best option regarding DLT and its complexity since one shot interaction is used without iterative bid matching and the simplicity of the matching algorithm.

The LW and the CQR of market DA and PCDA are the same and close to the results of the CDA. However, the difference in the performances of the market models is evident hourly-wise. Table 5 shows the corresponding market-clearing results. For ease of representation, only hour 12^{th} is reported. Table 5 presents the market results as pairings between participants, divided into three columns. The first represents the contract number signed by each participant. Some market participants sign several contracts at the same hour, and this is represented as b1-2, indicating that this is the second contract signed by participant b1. The other two columns contain the sale and/or purchase price and the quantity agreed for that contract. An in-depth analysis of the 12^{th} hour shows that the distributed CDA market allows actor s4, linked to node 1, to sell energy by creating a peer contract. This is not the case in the DA and PCDA markets, as they resolve the market once all bids have been collected. Hence, in the CDA market, the offer from actor s4 arrives after the first market clearing, together with other purchase requests. This series of events allows actor s4 to sell energy at the next market clearing. Contrarily, in the DA and PCDA markets, actor s4 is left outside, preventing him from selling the excess energy. The difference in energy that is cleared between the markets is 2.37 kWh.

Clear book CDA – 12^{th} hour			**Clear book DA – 12^{th} hour**			**Clear book PCDA – 12^{th} hour**		
# Contract	Price [EUR/kWh]	Quantity [kWh]	# Contract	Price [EUR/kWh]	Quantity [kWh]	# Contract	Price [EUR/kWh]	Quantity [kWh]
b1-1	0.294	2.301	*b1*	0.197	2.337	*b1*	0.246	2.337
b1-2	0.246	0.036	*b2*	0.197	2.337	*b2-1*	0.192	1.596
b2	0.203	2.337	*b3*	0.197	2.337	*b2-2*	0.203	0.741
b3	0.269	2.337	*b4*	0.197	3.506	*b3*	0.198	2.337
b4	0.180	3.506	*b5*	0.197	1.725	*b4*	0.191	3.506
b5-1	0.167	0.392	*b6*	0.197	4.082	*b5*	0.178	1.725
b5-2	0.178	0.665	*b7*	0.197	0.079	*b6-1*	0.174	1.860
b7	0.173	5.442	*s1*	0.197	3.933	*b6-2*	0.211	2.222
b8	0.172	1.725	*s2*	0.197	10.169	*b7*	0.210	0.079
s1-1	0.246	0.036	*s3*	0.197	2.301	*s1-1*	0.246	2.337
s1-2	0.180	3.506				*s1-2*	0.192	1.596
s1-3	0.167	0.392				*s2-1*	0.203	0.741
s2-1	0.203	2.337				*s2-2*	0.198	2.337
s2-2	0.173	5.442				*s2-3*	0.191	3.506
s2-3	0.172	1.725				*s2-4*	0.178	1.725
s2-4	0.178	0.665				*s2-5*	0.174	1.860
s3	0.294	2.301				*s3-1*	0.211	2.222
s4	0.269	2.337				*s3-2*	0.210	0.079

Table 7. Clearing results for the three markets at 12th hour - scenario A.

Table 7 shows that in the DA market final solution may disadvantage a user but improve the community benefit. Considering the CWT, Figure 5 shows the median, maximum, and minimum values for the clearing time of the three market models implementations. As can be seen, the DA and PCDA implementations show a little range of variation for the CWT as market clearing is addressed with a defined periodicity due to the intrinsic market design features. In contrast, the CDA market implementation shows the largest waiting time variance. However, the third quartile parameter of the CDA market guarantees lower CWT values times than the other two market types, given that the market is continuously cleared as soon as the bids are submitted to the platform.

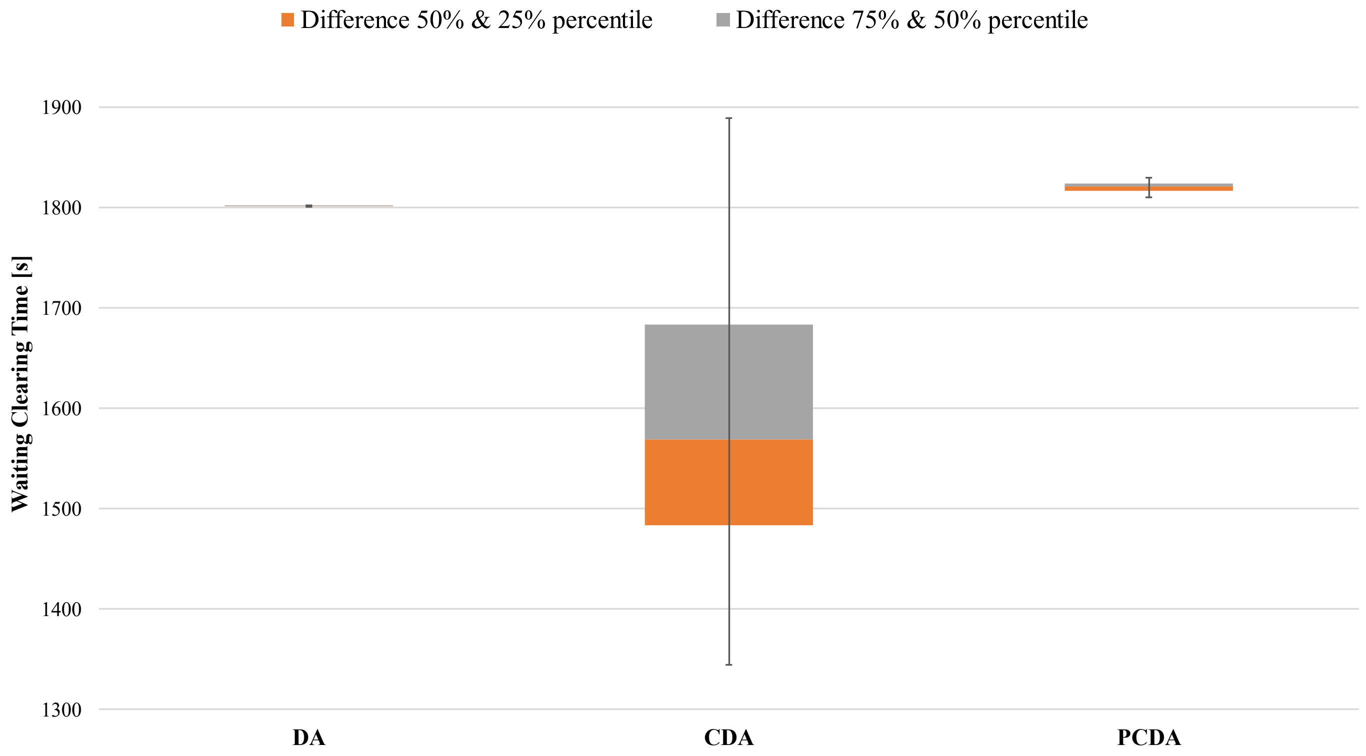

Fig. 5. Waiting Clearing Time average results - scenarios A.

Tables 8 and 9 show the blockchain-based complexity values $\boldsymbol{\alpha}$ and $\boldsymbol{\delta}$ for the functions required to develop the three market models on the blockchain platform. Specifically, the necessary functions are the same as presented in section 3.1. Since the three markets are distinguished primarily by how the market is cleared, the “Register participant”, “Place bid” and “Transfer money” functions are identical for the three market models. The $\boldsymbol{\alpha}$ and $\boldsymbol{\delta}$ values for these functions are shown in Table 8, along with the cost in euros that would be required to call those functions with only one bid placed in the market. The equivalent cost in euro is subject to great volatility related to the value of the Ethereum cryptocurrency [58], hence, in this paper the operating cost of the blockchain platform is considered in terms of GC rather than its equivalent value in euros. As an example, Table 8 and Table 9 report the costs using the 2022 conversion factor and the 2020 conversion factor. For simplicity the assessment of the complexity of the Ethereum blockchain platform developed reported in Table 8 and Table 9 concerns a single call to the functions in a single hour, as a more comprehensive statistical analysis would have been excessively time-consuming.

Table 8. Blockchain-based complexity and cost for “Register Participant”, “Place Bid” and “Transfer Money” functions.

	CPX [$\boldsymbol{\alpha}$+ $\boldsymbol{\delta}$]	**Gas** [Gas units]	**Cost (2020)** [EUR]	**Cost (2022)** [EUR]
Register Participant	199	52690	0.299	0.742
Place Bid	818	276149	1.57	3.89
Transfer Money	1099	190395	1.082	2.682

Table 9. Blockchain-based complexity and cost for “Clearing Market” function.

	DA	**CDA**	**PCDA**
CPX [$\boldsymbol{\alpha}$+ $\boldsymbol{\delta}$]	6355	6762	3747

Gas [Gas units]	476351	497896	402144
Cost (2020) [EUR]	2.708	2.832	2.287
Cost (2022) [EUR]	6.708	7.014	5.665

4.3 Results and discussion: Scenario B (with congestions)

As described in section 3, in the case of a network constraint violation a CMM is executed sequentially with respect to the energy market model. The energy market model operation that precedes CMM does not change, hence, the discussion in section **¡Error! No se encuentra el origen de la referencia.** given for scenario A applies. Therefore, in the following only the aspects related to the market implementation performances strictly related to the CMM are discussed.

Table 10 shows the results of Scenario B, which includes the CMM solutions. Table 10 shows that the implementation of LEM models exhibits a similar trend in Economic, Technical-Market, and Digitalization performances between scenario B and Scenario A. Therefore, the three market models for the analyzed case study maintain their performance as the electrical network's operating conditions change. DA and PCDA market performances are equivalent due to their similar market operation behavior with and without grid violations. Moreover, in that case of violations, the amount of flexibility accepted and the final cost for flexibility delivered is the same as both markets have the same trading period (i.e., 1 hour); the same quantities are traded in the market, and the flexibility prices are the same, leading the CMM to the same result.

Table 10. Comprehensive results (Scenario B).

	KPI	DA	CDA	PCDA
LW	Local Welfare [EUR]	23.953	23.395 (-2.33%)	23.953 (0%)
CQR	Clear Quantity Ratio [%]	25.621	27.906 (+8.92%)	25.621 (0%)
WCT	Waiting Clearing Time [min]	30.440	27.901 (-8.34%)	30.740 (+0.98%)
CPX	Complexity [$\boldsymbol{\delta}$+$\boldsymbol{\alpha}$]	9154	9696 (+5.92%)	6681 (-27.02%)
GC	Gas Cost [Gas]	1271598	1293279 (+1.71%)	1197527 (-5.83%)
FV	Flexibility Volume [kWh]	42.489	42.114 (-0.88%)	42.489 (0%)
FC	Flexibility Cost [EUR]	18.691	18.850 (+0.85%)	18.691 (0%)

Scenario B shows that the flexibility cost for the CDA market is higher than for the other market models, and the quantity delivered is lower, since a smaller number of users are eligible for offering flexibility as the market is continuously cleared. Fig. 6 shows the flexibility potential that the users make available throughout the day for the three markets (i.e., DA, CDA, and PCDA).

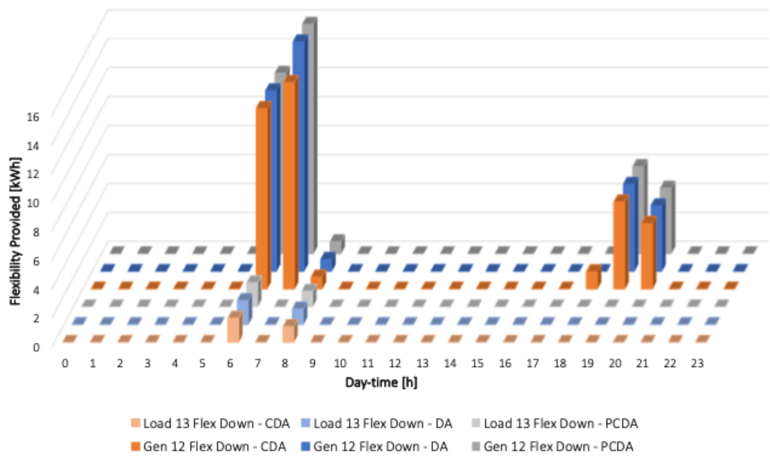

Fig. 6. Flexibility results throughout the day.

As illustrated in Fig. 6, the only flexibility involved is the downward flexibility of the generator in node #12 and the downward flexibility of the load in node #13. This is due to the congestion in scenario B in lines 11-12 and 12-13. As a result, only users 11, 12, and 13 may provide services to alleviate congestion. However, only users 12 and 13 are selected as providers since provider 11's sensitivity to the congested line 11-12 is lower than providers 12 and 13.

4.4 Discussions with existing literature

To clarify the efficiency of our results, we have compared our findings with those present in the existing literature. Given the different studies and scenarios considered between this study and those found in the literature, the following sections will generally discuss the key common areas across the different studies while addressing gaps that were not previously considered.

- *Economic Metrics*: Economic indicators consistently show better results for double auction models. As shown in [28], the proposed double auction model achieves up to 21% more social welfare than the uniform double auction model. In [30], the result shows an increase of 22.31% in average hourly social welfare for the proposed double auction algorithm. Furthermore, in [42], social welfare is improved by 16.5% compared to the auction-based model used as a reference. In this study, the same concept is repeated; indeed, local welfare values are higher compared to the continuous auction-based model.

- *Computational Time*: The use of this metric varies greatly between different studies. For example, in [26], the computational time evaluation considers clearing and settlement. In contrast, in this study, settlement time is excluded, but the waiting time for an offer to be accepted in the market is included. Additionally, in [32], the evaluation is separated for each function call. These differences make it difficult to compare with other studies; however, it is possible to determine that the average results across the various studies and this paper show that operations on the distributed platform are within the range of 1-2 seconds.
- *Market Complexity*: The concept of market or platform complexity is often associated with the cost of the market or platform. Compared to the model in [32], where market complexity was analyzed only through the cost in GAS units, the present study achieves a 17% improvement in managing the initial market phases such as participant registration and bid definition. Regarding the clearing mechanism, there is an improvement of 150% and 50% compared to the study proposed in [35]. However, compared to the algorithm proposed in [33], this study shows a 1% higher cost in GAS units. This difference lies in the management of processes on the platform. In [33], the algorithm adopts fewer cycles but employs more data structures useful for saving information on the platform. In this case, the introduction of the computational load of the distributed platform highlights this difference. Indeed, from a computational perspective, a cycle may be less burdensome than using a data structure. However, this information is often lost in many studies, as the evaluation of platform computational load is missing.
- *Network Constraints*: Previous works, such as [44] and [45], do not fully integrate network constraints into the evaluation of LEM performance. Aside from deviations from nominal values, no further evaluations are provided. In contrast, in this study, network constraints are used to demonstrate how the choice of one model over another can influence the costs associated with network constraint violations.

It is clear that many metrics proposed in different scenarios produce similar results. An example is provided by economic metrics, which show the same trend across different studies, and computational time metrics, which, although conceptually different between studies, have similar average values across all the studies. On the other hand, other metrics differ significantly, such as market complexity, which is represented differently across the various studies.

5 Conclusion

The paper proposes a techno-economic assessment of three different double-sided market models: double auction (DA), continuous double auction (CDA), and pseudo-continuous double auction (PCDA). The DA, CDA and PCDA market models are realized in a distributed manner via the blockchain platform to address the comparative assessment. The three market models include constraint violations management, which is solved using a linearized centralized optimization problem that involves flexibility service providers.

Simulations show that different market models can be developed and executed on the blockchain. The study proves that the DLT ensures that market models can be implemented in a fully distributed manner, in which the distributed platform has a pivotal role in the process. In addition, the study implements a techno-economic evaluation of different market models, considering their implications in terms of blockchain-based complexity LEM operational and management costs of the network violations. These results could interest policymakers, energy communities, and stakeholders interested in creating a LEM. For the analyzed case study, it is self-evident that no market outclasses the others. The DA market reduces LEM operational cost (expressed in terms of Gas) by 2% compared to a distributed CDA market but fails compared to a distributed PCDA market by 7%. In addition, a DA market reduces blockchain-based complexity, as measured by the number of transactions, by 4% compared to a distributed CDA market but is clearly at a 30% disadvantage compared to a distributed PCDA market.

In conclusion, the results show that a CDA market may require higher costs for flexibility, given its characteristic of market clearing, which occurs continuously several times in a single interval. Therefore, based on the results obtained, blockchain technology, in its current state of development, seems only partially suitable for P2P energy transactions. In particular, the gas cost characteristic and the influence of the cryptocurrency market severely limit blockchain technology deployment. Therefore, DLT can be an added value for LEMs if transaction costs are significantly reduced. A promising development could be DLT without cryptocurrencies like IOTA. Further study developments focus on managing the uncertainties that characterized the proposed case study. Additionally, the vehicle-to-grid mode of operation of the EVs will be included.

Although the study presents exploitable results, it is essential to acknowledge certain limitations. Privacy and scalability are among the most significant problems of blockchain-based solutions. The full replication of data and operations on all blockchain nodes complicates privacy and limits scalability. Additionally, it is important to note that the average block capacity on Ethereum is 15 million gas, limiting the number of transactions that can be processed. Lastly, with the gas price regularly exceeding 50 GWei, placing a single bid cost about €30, while clearing costs around €75. These significant costs impact the economic feasibility and welfare analysis. Additionally, it must be pointed out that the implemented market platforms are prototypes designed for proof of concept, suggesting the need for further enhancements for applications in pilot projects or on a larger scale. However, the results obtained may be scalable in terms of number of transactions and network size. The results presented are valid for the network and scenario tested, so replicability analysis should be considered considering different networks and scenarios. The market models are not affected by network characteristics, and their results can be considered generally valid, but this statement needs to be tested through simulations.

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Data Availability

The smart contract source code are provided in this GitHub repository: https://github.com/MarcoGalici/TechnoEconomic_Analysis_P2P_Market_Models_on_DLT.git.

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