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# Integrated prosumers–DSO approach applied in peer-to-peer energy and reserve tradings considering network constraints

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ABSTRACT

In recent years, there has been an increase of Renewable Energy Sources (RES) in energy markets that has to lead their agents to become more proactive. In this scenario, a market structure based on Peer-to-Peer (P2P) transactions is very promising but presents challenges for the network operation. A critical challenge is to ensure that network constraints are not violated due to energy trades between peers and neither due to the use of reserve capacity. In this paper, it is proposed a new iterative sequential approach for energy and reserve P2P market that ensures the feasibility of both energy and reserve transactions under network constraints. The methodology considers the interaction between the prosumers and the Distribution System Operator (DSO) in making the final market/operation decision and can be integrated into the existing distribution system. The proposed approach includes the estimation of reserve requirements based on the RES uncertain behavior from historical generation data, which allows identifying RES patterns. The proposed model is assessed through a case study that uses a 14-bus system, under the technical and economic criteria. The results show that the approach can ensure a feasible network operation encompassing energy and reserve markets.

## 1. Introduction

### 1.1. Motivation

The renewable and decentralized energy sources are changing the power system operation perspective [1]. The prosumers' figure is gaining prominence in this scenario. These individual agents have been playing a more active role in power systems and energy markets [2,3].

One of the most promising solutions to take advantage of this new perspective is the so called Peer-to-Peer (P2P) trading mechanisms, where prosumers can negotiate with each other in a distributed fashion. A complete review of P2P markets, challenges and suggestions for their proper implementation in power systems are done in [4–7].

In addition to the application of P2P to energy markets, this market design can also be applied in the context of the energy reserve market [8]. The reserve helps system operators to maintain a reliable electrical system, by dealing with supply and demand imbalances and supporting the system restoration after eventual outages [9]. With the advance of RES participation in power systems, the reserve requirement becomes more important to manage the variability and uncertainty inherent to this generation [10]. Although storage using batteries at the consumer/prosumer level can be a possible solution to mitigate RES uncertainty, it still represents a high investment.

The system operator is currently responsible for acquiring the necessary reserve to ensure the power system security. The increase of RES leads to an increase in reserve requirements and even in costs. In the near future, it is expected that RES agents should predict how much uncertainty they will bring and be responsible for compensating that. In addition, the system operator should be responsible for the decision on dispatching the contracted reserve. Thus, RES agents might negotiate the reserve they need in a P2P market, taking into account that this mechanism can provide only trades between peers, but in principle without impacting the existing system operation mechanism. Thus, it is relevant to develop a methodology capable of verifying whether the operation of the distribution network will be feasible when the system operator needs to make use of the reserve that was negotiated between the peers. As this approach can model the interaction between prosumers and the DSO, it can help build the basis for a fully decentralized and independent market.

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### 1.2. Literature review

Several works on P2P energy markets have been published in recent years. The authors of [11] propose two distinct P2P approaches, one where interactions between peers are resolved centrally by the utility, while the other is entirely peer-centered. Both base the calculation of charges for the distribution network's use on Distribution Locational Marginal Prices (DLMP). Another study [12] incorporates probabilistic DLMP with P2P as an alternative to traditional retail pricing. Tushar et al. [13] proposes a P2P scheme that can help the centralized power system to reduce its customers' total electricity demand during peak hours. Vieira and Zang [14] explore the use of blockchain technologies and auction mechanisms to facilitate autonomous P2P energy trading in microgrids. The authors of [15] present a novel management system that facilitates the P2P energy trading between prosumers in a decentralized way by coordinating the operation of distributed shiftable home appliances and battery systems. Chen et al. [16] propose a P2P energy sharing framework that takes into account the dynamic network structure, having the purpose of incorporating the network operator into the energy sharing process, improving the network structure and reducing the power losses. Azim et al. [17] study the applicability of P2P energy trading in a grid-tied network to understand the financial impact of this market design, and thus demonstrate the relevance of taking into account issues related to power network while designing a practical P2P trading scheme.

Guerrero et al. [18] propose a methodology based on sensitivity analysis to assess the impact of P2P transactions on the network, ensuring that energy exchanges do not violate network constraints. In contrast, Orlandini et al. [19] propose a coordinating methodology between the DSO and the P2P market operator, iteratively penalizing exchanges between peers that may cause congestion problems, assigning them a network tariff. In another work, Guerrero et al. [20] investigate P2P energy trading driven by the electrical distance between the peers. The DSO determines the shortest path between peers by using preference lists.

Heo et al. [21] propose an operator-oriented P2P energy trading scheme, where the operator decides the price and trading schedule instead of each participant. According to the authors, this methodology can be applied to existing distribution systems to reduce barriers for P2P trades.

Briefly, most works consider some other aspects together with bilateral energy transactions. The studies in [22–24] take into account aspects related to distribution networks. Product differences and peers' preference are covered in [22,24,25]. Flexible demand and uncertainty associated with local generation are discussed in [26]. Other P2P market-related topics comprising blockchain [27,28], electric vehicles [28,29], microgrids [30–32], and ancillary services [33,34] have been addressed in literature. However, trading energy reserve also by applying a P2P mechanism is considered only in [8], and a feasible network operation under any reserve capacity scenario is not guaranteed. Thus, to the best of our knowledge, none of the existing works considers a P2P energy and reserve market that guarantees not only the power flow and network constraints for the energy but also the viable operation under any reserve use.

### 1.3. Main contributions

Following the operator-oriented philosophy and aiming at solving the previous problem, the present work proposes an approach that is able to establish an adequate energy and reserve market, through a P2P mechanism that considers the requirement for a feasible power system operation. In particular, the proposed approach allows DSO to determine whether the energy and reserve transactions carried out between peers are feasible under the electrical grid constraints, as well as the adjustments in trades to make the system operation feasible.

Based on the energy and reserve markets of European countries, which are sequential [35], the proposed methodology aims to offer an alternative solution that fits the currently available regulation and that serves as a transition to a more decentralized environment in the future. In the present proposal, peers are free to trade, however the DSO (or manager) is the one who analyzes whether corrections need to be made in the market to achieve a viable network operation in the end.

In addition, the presented method also includes an approach to handle RES uncertain generation through historical generation data. These uncertainties could also be addressed with the use of Gaussian distribution [36] or even by versatile distribution as in [8]. The present approach estimates the reserve required to cover the RES uncertainty from historical generation data, by using two different algorithms for comparison purpose: (i) the well-known Monte Carlo Simulation (MCS) [37]; (ii) the new clustering algorithm of [38,39], called "modified Iterative Self-Organizing Data Analysis Technique Algorithm" (m-ISODATA).

So, the main contribution of the present paper is a novel integrated prosumers–DSO approach applied in an iterative sequential energy and reserve P2P market that is able to ensure that all tradings meet the network operating constraints. From the proposed solution, all energy and reserve transactions are technically feasible, even for the system's worst reserve scenario (use of the entire negotiated reserve.)

### 1.4. Structure

In addition to this introductory section, the paper is organized into four other sections. Section 2 provides the necessary background on P2P markets; Section 3 presents the iterative P2P market approach for energy and reserve negotiation; Section 4 evaluates the proposed model by using a well-known 14-bus distribution system and one-year data set; and Section 5 provides the main conclusions.

## 2. P2P fundamentals

To solve the energy problem of P2P transactions, the general mathematical formulation of the so-called *Full P2P market* presented in [4] was used along with the Product Differentiation (PD) concept defined by [25]. This market design is based on peers trading electricity directly with each other, considering the purchasing preferences, defined by PD, of each peer.

Therefore, the basic mathematical formulation of the energy problem can be defined as (1a)–(1e) for every period $t \in T$:

$$\min_{D} \sum_{n\in\Omega} \left[ C^{E}_{n,t}\left(E_{n,t}\right) + \tilde{C}^{E}_{n,t}\left(\varepsilon_{n,t}\right) \right] \forall t \in T \tag{1a}$$

$$\text{s.t.} \quad \underline{E_{n,t}} \leq E_{n,t} \leq \overline{E_{n,t}} \quad \forall n \in \Omega, \forall t \in T \tag{1b}$$

$$E_{nm,t} + E_{mn,t} = 0 \quad \forall (n,m) \in (\Omega, \omega_n), \forall t \in T \tag{1c}$$

$$E_{nm,t} \geq 0 \quad \forall (n,m) \in (\Omega_p \cup \Omega_r, \omega_n), \forall t \in T \tag{1d}$$

$$E_{nm,t} \leq 0 \quad \forall (n,m) \in (\Omega_c, \omega_n), \forall t \in T \tag{1e}$$

where $D = (E_{n,t} \in \mathbb{R}^{|\omega_n|})_{n\in\Omega}$, $E_{n,t}$ is the net energy injection of each agent $n \in \Omega$ at time $t$ and $E_{n,t} = \sum_{m\in\omega_n} E_{nm,t}$, with $E_{nm,t}$ corresponding to the energy exchange between peers $n$ and $m$ at time $t$, for which a positive value means sales/production (1d) and a negative value corresponds to a purchase/consumption (1e). $\Omega$, $\Omega_p$, $\Omega_r$ and $\Omega_c$ as sets for all peers, conventional producers, renewable producers, and consumers, respectively (hence $\Omega_p$, $\Omega_r$ $\Omega_c \in \Omega$, $\Omega_p \cap \Omega_r \cap \Omega_c = \emptyset$). The set $\omega_n$ contains the trading partners of a certain peer $n$. Bilateral negotiations $E_{nm,t}$ have the property of reciprocity, as defined by (1c). $\underline{E_{n,t}}$ and $\overline{E_{n,t}}$ are the boundaries of energy (1b). It is noteworthy that the dual variable $\lambda^{E}_{nm,t}$ associated with the exposed problem represents the price for each bilateral trade at time $t$.

The objective function (1a) has two components. The function $C^E_{n,t}\left(E_{n,t}\right)$, shown in (2), corresponds to the energy production cost and in this work a quadratic function is used as in [40].

$$C^E_{n,t}\left(E_{n,t}\right) = \frac{1}{2}\cdot ae_n \cdot E^2_{n,t} + be_n \cdot E_{n,t},\ ae_n, be_n \geq 0, \forall t \in T \tag{2}$$

For producers, this function reflects the production cost of energy $E_{n,t}$, while for consumers it represents how much they are willing to pay for $E_{n,t}$. It is noteworthy that it is quite common to model such cost functions in a quadratic form [4,23,25,40]. According to [25], such functions are seen as realistic for a large class of conventional generators, small consumers and prosumers.

From [40], $ae_n$, $be_n \geq 0$; $E_{n,t} \geq 0$ for producer and $E_{n,t} \leq 0$ for consumer. In case of producer, the function reflects the cost to produce $E_{n,t}$, whereas for a consumer, it represents the amount the load is willing to pay for $E_{n,t}$.

The second component of the objective function is shown in (3).

$$\tilde{C^E_{n,t}}\left(\varepsilon_{n,t}\right) = \sum_{m\in\omega_n}\left(C^{PD}_{nm,t}\cdot E_{nm,t}\right) \quad \forall t \in T \tag{3}$$

where $\varepsilon_{n,t} = \left(E_{nm,t}\right)_{m\in\omega_n}$ and the coefficient $C^{PD}_{nm,t}\left(\varepsilon_{n,t}\right)$ is the PD criteria, being able to consider emissions, distance and peer reputation. For example, the distance criterion would represent that peer $n$ is more willing to negotiate with their physically closer peers $m$, which can encourage energy consumption from local producers and is the criterion used in this work. The reader is referred to [25] for more details. It is worth noting, however, that the use of a combination of different PDs presents a great challenge. Correctly sizing the weight of each penalty is complex, deserving a dedicated study for this purpose.

In this type of market, it is extremely important to know which peer is responsible for a possible violation of the pre-established network constraints. To this end, a power flow tracing method is implemented, which allows determining the contribution that each peer has on all network's lines, as proposed in [41]. This method has been chosen due to its good performance for distribution grids with high penetration of distributed energy resources and bidirectional power flow [42]. Though, through this method, each generator/consumer is penalized based on its impact in the line overload.

## 3. Proposed methodology

### 3.1. Determining reserve

How to properly represent the RES uncertainty is a complex problem. Generally, a Gaussian distribution [36] is used for this task. However, [8] points out that many studies have shown that this method cannot always model uncertainty accurately, suggesting that data mining approaches can be pursued. Thus, this work carried out a data mining analysis to represent the RES uncertainty, considering one year and 30 min time-step based on available Australian data set [43,44]. More precisely, the production levels of three wind turbines and two photovoltaic (PV) plants are considered.

Two algorithms are applied and compared, MCS and m-ISODATA, and two analyzes are performed for each method:

- Case 1: complete analysis with all data in the series, and
- Case 2: analysis of the generation history only for a specific hour (12 o'clock) on different days.

#### 3.1.1. Monte Carlo Simulation algorithm

The MCS is a widely used algorithm to deal with stochastic variables due to its simplicity and high precision [45]. It is a sampling method based on the Probability Density Function (PDF) of stochastic variables that requires a large number of simulations with randomly chosen input values [46].

In the present work, the Weibull PDF for wind peers [47] and Beta PDF for PV peers [48] are used. After estimating the PDFs for each renewable peer in each of the proposed cases, the Cumulative Distribution Function (CDF) is obtained (Fig. 1), which enables generating random samples of renewable generation for the MCS.

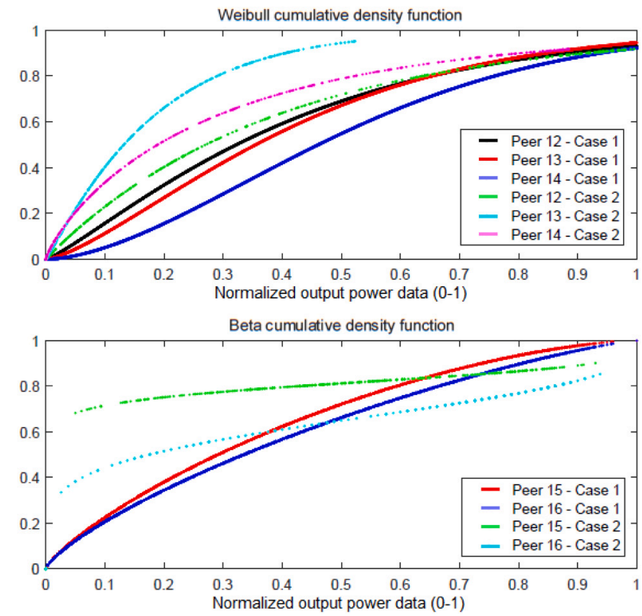


**Fig. 1.** Cumulative distribution functions.

The shape ($\beta$) and scale ($\eta$) parameters of the Weibull distribution, as well as the shape parameters ($\alpha$ and $\beta$) for the Beta distribution were calculated for the two cases and renewable peers by using the maximum likelihood estimation method [49], as shown in Table 1.

The $x$-axis of Fig. 1 has normalized data in range [0–1] that are obtained by dividing each generation value by the respective value of $E_{n,t}$. Thus, the data are normalized in relation to $E_{n,t}$ and value '1' refers to $E_{n,t}$. Therefore, the expected value from the CDF function, $E^{MCS}_{n,t}$, is limited according to (4) since every sample from Fig. 1 is limited to $E_{n,t}$.

$$0 \leq E^{MCS}_{n,t} \leq E_{n,t} \quad \forall n \in \Omega_r, \forall t \in T \tag{4}$$

By using the CDFs and applying MCS, the reserve required to cover the uncertainty can be calculated by (5).

$$R_{n,t} = E^{MCS}_{n,t} - E_{n,t} \quad \forall n \in \Omega_r, \forall t \in T \tag{5}$$

From (4) and (5), renewable generators have $R_{n,t} \leq 0$ because they need to buy reserve capacity from the market.

#### 3.1.2. m-ISODATA clustering algorithm

The m-ISODATA is a unsupervised clustering algorithm proposed recently by de Paula et al. [38]. This algorithm seeks to capture representative scenarios to represent uncertainties in power system models. One advantage is the ability to automatically obtain the number of scenarios needed to fully capture the historical series' variability. In the present paper, the m-ISODATA clustering method is applied to generate $k$ scenarios that best represent the historical data. Each scenario consists of a centroid associated with a probability of occurrence. Then, the analysis and clustering of the data from each generator allows predicting the Generator's Behavior Pattern (GBP[2]) of each renewable peer.

[2] GBP refers to the behavior pattern of a given generator over time. Such a pattern is found from constant measurement and analysis of the real generation values.

**Table 1**
Weibull and Beta distributions parameters.

| Case | Peer 12 | | Peer 13 | | Peer 14 | | Peer 15 | | Peer 16 | |
|---|---|---|---|---|---|---|---|---|---|---|
| | $\beta$ | $\eta$ | $\beta$ | $\eta$ | $\beta$ | $\eta$ | $\alpha$ | $\beta$ | $\alpha$ | $\beta$ |
| 1 | 0.438362 | 1.19391 | 0.463088 | 1.38261 | 0.573135 | 1.68556 | 0.79392 | 1.52982 | 0.75537 | 1.23097 |
| 2 | 0.39294 | 0.981467 | 0.185981 | 1.06869 | 0.294587 | 0.828193 | 0.064068 | 0.267465 | 0.201679 | 0.358648 |

**Table 2**
M-ISODATA scenarios of the renewable generators (GBP).

| Peer 12 (Wind) | | | | Peer 13 (Wind) | | | | Peer 14 (Wind) | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Case 1 | | Case 2 | | Case 1 | | Case 2 | | Case 1 | | Case 2 | |
| Energy [p.u. MWh] | Probability [%] | Energy [p.u. MWh] | Probability [%] | Energy [p.u. MWh] | Probability [%] | Energy [p.u. MWh] | Probability [%] | Energy [p.u. MWh] | Probability [%] | Energy [p.u. MWh] | Probability [%] |
| 0,0141 | 7,60 | 0,0219 | 15,62 | 0,0253 | 7,12 | 0,0280 | 0,1753 | 0,0349 | 6,01 | 0,0160 | 0,1945 |
| 0,4483 | 5,83 | 0,4805 | 5,48 | 0,4387 | 5,77 | 0,3828 | 0,0466 | 0,5325 | 6,08 | 0,4179 | 0,0493 |
| 0,2115 | 7,11 | 0,1960 | 6,85 | 0,2121 | 7,11 | 0,1437 | 0,0904 | 0,2871 | 5,94 | 0,1323 | 0,0877 |
| 0,7971 | 6,60 | 0,8604 | 4,93 | 0,7103 | 7,64 | 0,6478 | 0,0658 | 0,8010 | 5,82 | 0,8229 | 0,0767 |
| 0,1106 | 7,62 | 0,0749 | 9,86 | 0,1164 | 7,10 | 0,0870 | 0,1068 | 0,1636 | 6,73 | 0,0747 | 0,1342 |
| 0,5913 | 5,70 | 0,6235 | 7,12 | 0,6206 | 7,21 | 0,5369 | 0,0630 | 0,6598 | 6,56 | 0,5800 | 0,0438 |
| 0,3213 | 6,66 | 0,3096 | 5,75 | 0,3194 | 6,90 | 0,2562 | 0,0658 | 0,4091 | 6,15 | 0,2615 | 0,0548 |
| 0,9009 | 7,18 | 0,9281 | 9,04 | 0,9380 | 8,12 | 0,9345 | 0,0521 | 0,9289 | 5,77 | 0,9218 | 0,0548 |
| 0,0598 | 6,73 | 0,2374 | 7,67 | 0,0713 | 7,85 | 0,4555 | 0,0712 | 0,1071 | 7,05 | 0,4951 | 0,0575 |
| 0,5181 | 5,47 | 0,1282 | 8,49 | 0,5163 | 6,56 | 0,1951 | 0,0877 | 0,5971 | 5,93 | 0,1950 | 0,0575 |
| 0,2651 | 6,87 | 0,7319 | 6,58 | 0,2649 | 6,80 | 0,7294 | 0,0521 | 0,3493 | 6,20 | 0,6699 | 0,0658 |
| 0,1614 | 7,35 | 0,3906 | 7,12 | 0,8001 | 8,28 | 0,3149 | 0,0521 | 0,8643 | 6,27 | 0,3413 | 0,0658 |
| 0,6821 | 6,46 | 0,9732 | 5,48 | 0,1637 | 7,17 | 0,7891 | 0,0712 | 0,2229 | 6,86 | 0,9866 | 0,0575 |
| 0,3819 | 6,36 | – | – | 0,3782 | 6,37 | – | – | 0,7307 | 5,78 | – | – |
| 0,9652 | 6,45 | – | – | – | – | – | – | 0,4713 | 6,06 | – | – |
| – | – | – | – | – | – | – | – | 0,9877 | 6,80 | – | – |

| Peer 15 (Solar) | | | | Peer 16 (Solar) | | | |
|---|---|---|---|---|---|---|---|
| Case 1 | | Case 2 | | Case 1 | | Case 2 | |
| Energy [p.u. MWh] | Probability [%] | Energy [p.u. MWh] | Probability [%] | Energy [p.u. MWh] | Probability [%] | Energy [p.u. MWh] | Probability [%] |
| 0.0266 | 17.78 | 0.0247 | 4.93 | 0.0285 | 16.69 | 0.1084 | 8.49 |
| 0.3691 | 6.36 | 0.597 | 10.96 | 0.4342 | 5.65 | 0.6566 | 7.67 |
| 0.1499 | 7.36 | 0.3721 | 7.12 | 0.181 | 5.42 | 0.3995 | 6.58 |
| 0.6262 | 5.8 | 0.7547 | 5.75 | 0.7008 | 6.48 | 0.8606 | 11.78 |
| 0.0889 | 10.76 | 0.2249 | 4.38 | 0.0794 | 7.21 | 0.2529 | 9.59 |
| 0.4912 | 6.07 | 0.6727 | 8.77 | 0.5774 | 5.1 | 0.8015 | 17.53 |
| 0.2548 | 5.9 | 0.4721 | 10.41 | 0.3001 | 5.54 | 0.5296 | 4.93 |
| 0.7793 | 5.95 | 0.8693 | 6.85 | 0.8127 | 6.89 | 0.9067 | 13.97 |
| 0.4293 | 6.51 | 0.1531 | 6.3 | 0.5045 | 5.61 | 0.7371 | 10.68 |
| 0.2029 | 5.91 | 0.4158 | 4.93 | 0.2363 | 6.1 | 0.9493 | 8.77 |
| 0.7007 | 5.24 | 0.8242 | 5.75 | 0.7564 | 6.1 | – | – |
| 0.5576 | 5.76 | 0.3022 | 6.85 | 0.131 | 6.37 | – | – |
| 0.3112 | 5.61 | 0.5203 | 10.96 | 0.6383 | 5.87 | – | – |
| 0.8643 | 4.98 | 0.9304 | 6.03 | 0.3619 | 5.61 | – | – |
| – | – | – | – | 0.8786 | 5.36 | – | – |

Therefore, the GBP for all five renewable peers of the cases under study is obtained by performing a data-driven analysis of the corresponding real generation data. In other words, the GBP consists of a simplified way to predict the future behavior of a specific generator from its past behavior. Table 2 shows the results obtained by the m-ISODATA clustering algorithm for all the renewable generators of the proposed case studies. In Table 2, the Energy [p.u. MWh] ($E^p_{n,k,t}$) is the normalized predicted energy according to the GBP at time $t$. This is normalized in terms of $E_{n,t}$, i.e., $E^p_{n,k,t} = 1$ refers to $E_{n,t}$. The Probability (%), $P(E^p_{n,k,t})$, is the probability of $E^p_{n,k,t}$.

From the GBP, the reserve required to cover the uncertainty is calculated by using (6) and (7). Eq. (6) calculates the expected energy $E^{mISO}_{n,t}$ that represents, according to m-ISODATA, how much energy peer $n$ can actually generate at time $t$. This is obtained by weighting the scenarios in terms of the respective predicted energy $E^p_{n,k,t}$ and probability $P(E^p_{n,k,t})$, where $n_c$ is the number of clusters. Eq. (7), in turn, allows the calculation of the required reserve for every renewable peer $n$ at time $t$.

$$E^{mISO}_{n,t} = E_{n,t} \cdot \sum_{k=1}^{n_c} \left[ E^p_{n,k,t} \cdot P\left(E^p_{n,k,t}\right)\right] \forall n \in \Omega_r, \forall t \in T \tag{6}$$

$$R_{n,t} = E^{mISO}_{n,t} - E_{n,t} \quad \forall n \in \Omega_r, \forall t \in T \tag{7}$$

where $E^{mISO}_{n,t}$ represents the expected energy to be generated by peer $n$ at time $t$. From (7), the reserve for a renewable generator is equal to the difference between the energy that this generator will actually generate, according to its GBP, and the energy that it negotiates in the energy market. Notice that $R_{n,t} \leq 0$ for renewable generators as previously described for Eq. (5).

### 3.2. Inclusion of the reserve into the P2P problem

The mathematical modeling used in Section 2 for the energy exchanges between peers can be extended to the reserve market. Thus, the formulation of the P2P reserve market can be defined as (8a)–(8e) [8] for every $t \in T$:

$$\min_{D} \sum_{n \in \Omega} \left[ C^R_{n,t}\left(R_{n,t}\right) + C^{\tilde{R}}_{n,t}\left(r_{n,t}\right)\right] \forall t \in T \tag{8a}$$

$$\text{s.t.} \quad \underline{R_{n,t}} \leq R_{n,t} \leq \overline{R_{n,t}} \quad \forall n \in \Omega, \forall t \in T \tag{8b}$$

$$R_{nm,t} + R_{mn,t} = 0 \quad \forall (n,m) \in (\Omega, \omega_n), \forall t \in T \tag{8c}$$

$$R_{nm,t} \geq 0 \quad \forall (n,m) \in (\Omega_g \cup \Omega_c, \omega_n), \forall t \in T \tag{8d}$$

$$R_{nm,t} \leq 0 \quad \forall (n,m) \in (\Omega_r, \omega_n), \forall t \in T \tag{8e}$$

where $D = (R_{n,t} \in \mathbb{R}^{|\omega_n|})_{n\in\Omega}$, $R_{n,t}$ is the reserve injection of each agent $n \in \Omega$ at time $t$ and $R_{n,t} = \sum_{m\in\omega_n} R_{nm,t}$, with $R_{nm,t}$ corresponding to the reserve exchange between peers $n$ and $m$ at time $t$, for which a positive value means sales (8d) and a negative value means a purchase (8e). Bilateral negotiations $R_{nm,t}$ have the property of reciprocity, as defined by (8c). $\underline{R_{n,t}}$ and $\overline{R_{n,t}}$ are the boundaries of reserve as in (8b). It is noteworthy that the dual variable $\lambda^R_{nm,t}$ associated with the problem represents the price for each reserve bilateral negotiation at time $t$. The cost function shown in (2) can be extended to reserve negotiation, thus the function $C^R_{n,t}\left(R_{n,t}\right) = \frac{1}{2} \cdot ar_n \cdot R^2_{n,t} + br_n \cdot R_{n,t}$, where $ar_n > 0$ and $br_n > 0$, corresponds to the reserve production cost. Similar to the energy market and according to (8a), the objective is to minimize the reserve's total cost of all bilateral trades carried out between the peers.

The reasoning about constraints (8d) and (8e) is similar to that explained for (1d) and (1e), as supported by [40]. In particular, $R_{n,t} > 0$ is an available reserve for selling and $R_{n,t} < 0$ means the need for buying additional reserve capacity from the market (in case of renewable generators, for instance). It can be highlighted that constraint (8e) is in accordance with constraints (5) and (7) in terms of a negative reserve for renewable generators.

An additional constraint (9) is required to ensure that no peer can negotiate an amount of energy plus reserve greater than its maximum generation capacity, in generators' case, or its maximum load flexibility in consumers' case.

$$\underline{E_{n,t}} \leq E_{n,t} + R_{n,t} \leq \overline{E_{n,t}} \quad \forall n \in \Omega, \forall t \in T \tag{9}$$

It is worth noting that despite not knowing, in advance, where the system reserve will be activated, the use of PD allows prioritizing the reserve negotiations between neighbors, thus in favor of local prosumers. So the function presented in (3) can also be extended to represent the peer's preference in reserve negotiation. Thus, $\tilde{C}^R_{n,t}\left(r_{n,t}\right) = \sum_{m\in\omega_n}(C^{PD}_{nm,t} \cdot R_{nm,t})$, where $r_{n,t} = \left(R_{nm,t}\right)_{m\in\omega_n}$.

The validation of the P2P transactions under network constraints is an important task for ensuring the feasibility of the P2P market solutions. The energy $E_{nm,t}$ and reserve $R_{nm,t}$ transactions between peers from the P2P market solutions are used to establish the energy $E_{n,t}$ and reserve $R_{n,t}$ setpoints for all peers, respectively, hence used by the Alternating Current Power Flow (AC-PF) to analyze grid conditions. Assuming that P2P transactions will occur in low and medium voltage distribution networks, an AC-PF model using pandapower package [50] is used.

The voltage level and maximum active power generation for each generator, as well as the load demand of each consumer, are predefined. The node representing the connection between the local community and the external network (upstream connection) is defined as the slack bus in pandapower. As physical network constraints, the limits for nodal voltage and line thermal condition are considered in (10) and (11), respectively.

$$V_i^{min} \leq V_{i,t} \leq V_i^{max}, \quad i = 1, \dots, n_i, \forall t \in T \tag{10}$$

$$I_{l,t} \leq I_l^{max}, \quad l = 1, \dots, n_l, \forall t \in T \tag{11}$$

where $V_{i,t}$ is the voltage at bus $i$ at time $t$; $V_i^{min}$ and $V_i^{max}$ are voltage limits, $n_i$ is the number of system buses; $I_{l,t}$ is the current of line $l$ at time $t$, $I_l^{max}$ is the maximum current capacity of line $l$, and, finally, $n_l$ is the number of lines in the system.

With the purpose of ensuring that the electrical network can support the negotiated reserve, the $R_{n,t}$ variable is inserted into the network power balance as virtual generators. Thus, a virtual generator is considered as connected to the network bus for every peer, having $R_{n,t} > 0$ for peers who sell reserves (conventional generators and consumers) or $R_{n,t} < 0$ for peers who buy reserve (renewable generators). Therefore, in the power balance equation (12), the active power injection (13) includes the powers related to the energy and reserve negotiated by the peers at bus $i$.

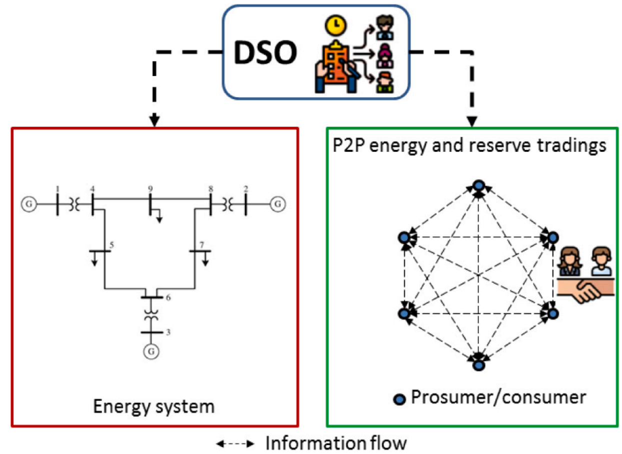


**Fig. 2.** Integrated prosumer–DSO framework.

$$\sum_{n\in\Omega} E^i_{n,t} + \sum_{n\in\Omega} R^i_{n,t} = \sum_{j\in\phi_i} P_{ij,t} \quad \forall i \in n_i, \forall t \in T \tag{12}$$

$$P_{ij,t} = V_{i,t} \cdot V_{j,t} \cdot \left(G_{ij,t} \cdot \cos\theta_{ij,t} + B_{ij,t} \cdot \sin\theta_{ij,t}\right) \quad \forall t \in T \tag{13}$$

where $E^i_{n,t}$ and $R^i_{n,t}$ are the power produced (or consumed) and the reserve, respectively, from peer $n$ that is connected to bus $i$ at time $t$; $\phi_i$ is the set of buses connected to bus $i$; $P_{ij,t}$ is the power flow through line $ij$ at time $t$; $G_{ij,t}$ and $B_{ij,t}$ are the conductance and susceptance at time $t$, respectively; $\theta_t$ is the voltage angle at time $t$ (with $\theta_{ij,t} = \theta_{i,t}$ - $\theta_{j,t}$).

### 3.3. Proposed iterative algorithm

This work proposes an iterative and sequential algorithm to solve the energy and reserve P2P market problem that takes into account the distribution grid operation and allows integration between peers and DSO. Fig. 2 illustrates the proposed integrated prosumer–DSO framework where the DSO is an independent agent responsible for maintaining the balance of energy and reserve in the distribution network while satisfying network constraints. The method has been designed to allow the system operator to penalize the generator or the consumer that causes voltage and congestion problems, with the purpose of encouraging them to renegotiate their bilateral energy/reserve trades in P2P markets.

It is worth mentioning that to penalize a generator, in this case, means limiting its maximum dispatch capacity, and penalizing a consumer, in turn, means limiting its maximum load demand. So, penalizing consumers has the same effect as reducing their energy consumption profile. This effect is known in literature as load flexibility and is an undesirable operational condition. Moreover, only consumers with a certain flexibility level are able to meet this profile. In light of the previous feature, the present work follows the strategy of penalizing generators, when necessary, instead of consumers.

Defining how much to penalize a peer can be tricky. To avoid an excessive penalty, the generator's power bid[3] must be decreased by a certain value $\delta$% at each iteration, where $\delta$ should not be a high value.

[3] In a P2P electricity market, the sellers and buyers submit bids for sell/buy energy. Bids represent how much power the sellers or buyers are willing to

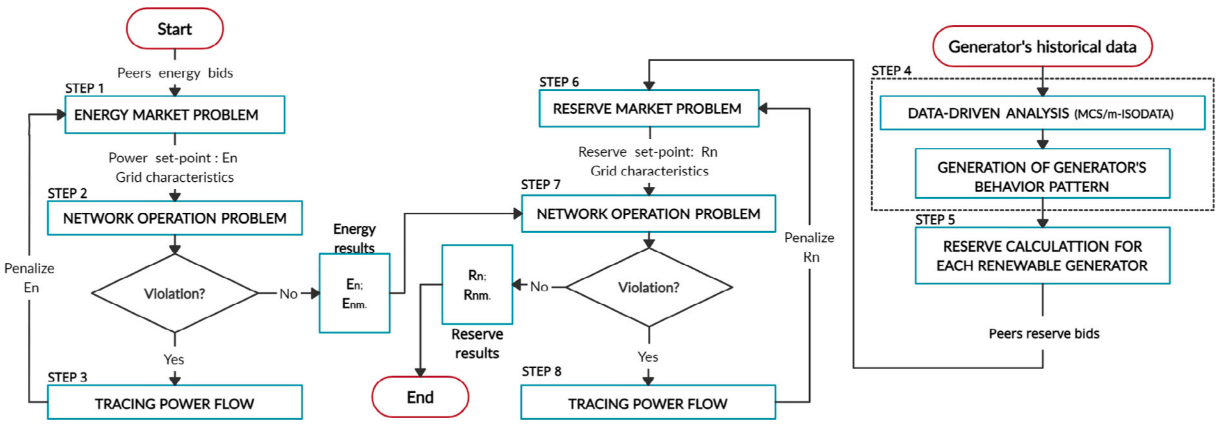


**Fig. 3.** Iterative methodology flowchart.

Fig. 3 gives the flowchart of the proposed iterative approach.

- **Step 1:** P2P energy market optimization (1a)–(1e) without considering network constraints. By analyzing the bids and purchase offers from all peers, the values of $E_{n,t}$ and $E_{nm,t}$ are calculated and used as input data for Step 2. In this step, peers can freely trade their energy, define their particular PD criteria and their individual preferences.
- **Step 2:** It consists of the network operation problem. Based on the $E_{n,t}$ and $E_{nm,t}$ values, the DSO checks the feasibility of the proposed transactions through an AC-PF, which determines the power flows $P_{ij,t}$ in all system lines $ij \in n_l$ and the voltage $V_{i,t}$ at all buses $i \in n_i$. If any line in the electrical network has current above the respective limit, thus violating constraint in (11), or any system bus has voltage out of its range, see constraint in (10), then Step 3 is performed to correct the violation by readjusting the bid of energy. Otherwise, the iterative process is stopped and the results $E_{n,t}$, $E_{nm,t}$ are displayed;
- **Step 3:** This step is formed by the power flow tracing algorithm from Bialek [51,52]. The algorithm is able to determine the specific use of each line in the network by each of the generators and consumers of the system, based on the proportional sharing principle. Usually, more than one prosumer could cause a bottleneck, as the lines of the network are not only used by one single user. Using the power flow tracing method, it is possible to simultaneously determine the share of each generator/consumer in the power flow of all lines in the system. In this way, knowing which line is overloaded, it is also known which generators/consumers are "responsible" for this overload. Then, we penalize each of them according to their share of use of the overloaded line. Based on the AC-PF results (Step 2), the algorithm determines the share of a specific generator in every line power flow $P_{ij,t}$. In other words, it means determining which peers make use of a specific system line or contribute to the violation of some constraints. Then, the DSO can penalize the power bid of the generator that caused the violation. The DSO can directly inform the peer who caused the violation that its bid must be readjusted. The notice could be a private message, for instance, via an online P2P trading platform. After Step 3, the algorithm returns to Step 1. If a generator is penalized for violating a network constraint, in the next iteration, this generator will necessarily negotiate less energy, thus it will alleviate the overload in the region of the system where it is located. Note that each generator contributing to line congestion is penalized according to its share in the use of that line.
- **Step 4:** When m-ISODATA is used, the generators' GBP is created from the generation historical data of renewable peers. From its own generation history, each peer can perform a data-driven analysis to create the GBP for itself and find the values of $E^{p}_{n,k,t}$ and $(PE^{p}_{n,k,t})$. When MCS is used, it finds the values of $E^{MCS}_{n,t}$.
- **Step 5:** With the values calculated in Step 4, the reserve values required by each renewable generator are calculated by them using (5) or (7).
- **Step 6:** Consists of the P2P reserve market optimization (8a)–(8e), and (9). From analyzing the reserve bids and purchase offers of all peers, the values of $R_{n,t}$ and $R_{nm,t}$ are calculated. These values coupled with $E_{n,t}$ and $E_{nm,t}$ are used as input data for Step 7. In this step, peers can freely trade their reserve, define their particular PD criteria and individual preferences, just as in Step 1.
- **Step 7:** Based on $E_{n,t}$, $E_{nm,t}$, $R_{n,t}$ and $R_{nm,t}$ values, the proposed transactions feasibility is checked by the DSO through an AC-PF, like in Step 2, by using (12). If any of the constraints is violated, the method goes to Step 8. Otherwise, the iterative process is stopped and the results $R_{n,t}$, $R_{nm,t}$ are displayed;
- **Step 8:** Similar to Step 3, in Step 8 the DSO determines which peers make use of a specific system line or contribute to the violation of constraints. Then, the DSO can penalize the generator's reserve bid that caused the violation and, after that, the algorithm returns to Step 6.

One highlight that is worth elucidating is that modeling an individual peer or an aggregator/community involving several peers is the same for the proposed methodology, and the method can be generalized to solar-centric or wind-centric generation profiles, since it only depends on the values that the peer intends to negotiate ($E_{n,t}$ and $R_{n,t}$). However, this paper aims to offer an alternative solution that fits the currently available regulation and that serves as a transition to a more decentralized environment in the future. The study focuses on a case in which the analysis is performed for a medium voltage network; therefore, the aggregation of residential consumers/prosumers is seen to be the first evolution of those markets.

Furthermore, we develop a case study where at least one generator of each type (wind, PV gas and coal) was represented and where the distribution lines were also overloaded, so that it was possible to show the proposed methodology performance. If several distributed generation units were spread out in the test system, the loads would be served locally (generation and load on the same bus), which would lead to low grid usage.

## 4. Case study

This section presents a case study showing the application of the proposed iterative approach and its performance.

trade and are usually presented in the form of a price and quantity quotation. This definition can be extended to reserve bid.

**Table 3**
Peers' parameters.

| Peer | Type | Energy | Bus | $E_{min}$ [MWh] | $E_{max}$ [MWh] | $ae$ [\$/MWh$^2$] | $be$ [\$/MWh] | $R_{min}$ [MWh] | $R_{max}$ [MWh] | $ar$ [\$/MWh$^2$] | $br$ [\$/MWh] |
|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 | Consumer | – | 2 | 3.54 | 3.93 | 1.18 | 50.9 | 0 | 0.4 | 0.6 | 25.5 |
| 2 | Consumer | – | 3 | 9.1 | 10.08 | 0.24 | 37.8 | 0 | 0.1 | 0.12 | 18.4 |
| 3 | Consumer | – | 4 | 6.21 | 6.89 | 0.57 | 43.6 | 0 | 0.69 | 0.28 | 21.5 |
| 4 | Consumer | – | 5 | 0.6 | 0.64 | 1.24 | 50.3 | 0 | 0.06 | 0.62 | 25.1 |
| 5 | Consumer | – | 6 | 2.96 | 3.28 | 1.62 | 30.4 | 0 | 0.32 | 0.8 | 15.2 |
| 6 | Consumer | – | 9 | 4.12 | 4.57 | 0.31 | 27.5 | 0 | 0.45 | 0.15 | 13.75 |
| 7 | Consumer | – | 10 | 1.01 | 1.12 | 4.36 | 46.7 | 0 | 0.11 | 2.15 | 23.4 |
| 8 | Consumer | – | 11 | 0.41 | 0.44 | 1.63 | 33.2 | 0 | 0.04 | 0.8 | 16 |
| 9 | Consumer | – | 12 | 0.41 | 0.44 | 5.16 | 55 | 0 | 0.04 | 2.6 | 27 |
| 10 | Consumer | – | 13 | 1.96 | 2.17 | 1.96 | 62.1 | 0 | 0.21 | 0.5 | 31 |
| 11 | Consumer | – | 14 | 2.18 | 2.25 | 1.54 | 42.9 | 0 | 0.22 | 0.8 | 21.5 |
| 12 | Producer | Wind | 2 | 0 | 47.0 | 0 | 0 | 16.44 | 16.44 | 0 | 1 |
| 13 | Producer | Wind | 3 | 0 | 7.2 | 0 | 0 | 3.67 | 3.67 | 0 | 1 |
| 14 | Producer | Wind | 8 | 0 | 3.18 | 0 | 0 | 1.36 | 1.36 | 0 | 1 |
| 15 | Producer | Solar | 2 | 0 | 3.87 | 0 | 0 | 1.58 | 1.58 | 0 | 1 |
| 16 | Producer | Solar | 6 | 0 | 6.57 | 0 | 0 | 1.62 | 1.62 | 0 | 1 |
| 17 | Producer | Gas | 2 | 0 | 20 | 2.51 | 27.7 | 0 | 10 | 0.753 | 8.31 |
| 18 | Producer | Coal | 3 | 0 | 50 | 0.15 | 35.5 | 0 | 25 | 0.045 | 10.65 |
| 19 | Producer | Gas | 8 | 0 | 10 | 3.64 | 30.4 | 0 | 5 | 1.092 | 9.12 |

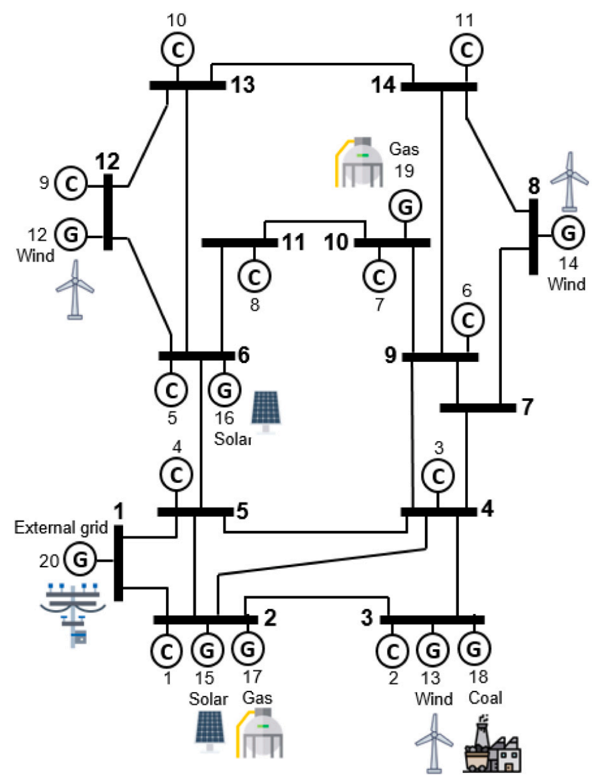


**Fig. 4.** Modified IEEE-14 bus system [41].

### 4.1. Case characterization

The case study is based on a modified 14-bus distribution network with 19 peers and a single external network connection [41], as illustrated in Fig. 4. This 13 kV medium voltage distribution network has $I_l^{max}$ = 0.6 kA for all lines $l \in n_l$; $V_i^{min}$ and $V_i^{max}$ are considered as 0.95 p.u. and 1.05 p.u., respectively, for every bus $i \in n_i$. The market operation horizon ($T$) is one hour and, thus, the subscript $t$ will be omitted in the variables $E_{nm}$ and $R_{nm}$ from this point.

In the iterative sequential P2P energy and reserve market, each peer can negotiate with any other, and each renewable peer can determine its necessary reserve, with the aid of the proposed GBP algorithm. Peers 1 to 11 are prosumers whose demand is greater than generation (consumers), while peers 12 to 19 are prosumers with generation surplus (producers).

The producers are categorized by their generation technology, and there are three wind turbines, two PV systems, two gas turbines and one coal based system. Peer 20 represents the external network connection, which can be, for instance, the local utility network or another energy community. The penalization factor $\delta$ is set at 1% to penalize peers as little as possible [41].

The peers' parameters are summarized in Table 3. Notice that the reserve cost coefficients are defined as smaller than the energy cost coefficients, $ar_n < ae_n$ and $br_n < be_n$, following the work in [8].

Finally, as the purpose is to analyze and promote local energy trading, electricity trade with the external grid is only allowed as a last resort. Thus, the price to import energy from the external grid is 150 \$/MWh, while to export energy is 10 \$/MWh.

**Table 4**
Reserve for all renewable generators.

| Case | m-ISODATA | | MCS | |
|---|---|---|---|---|
| | 1 | 2 | 1 | 2 |
| $R_{12}$ [MWh] | 16.44 | 16.96 | 16.52 | 16.99 |
| $R_{13}$ [MWh] | 3.67 | 4.04 | 3.57 | 5.06 |
| $R_{14}$ [MWh] | 1.36 | 1.75 | 1.34 | 1.85 |
| $R_{15}$ [MWh] | 2.18 | 1.58 | 2.19 | 2.69 |
| $R_{16}$ [MWh] | 2.95 | 1.62 | 3.01 | 3.11 |

### 4.2. Determining reserve needs

Firstly, it is necessary to calculate the reserve amount that each renewable generator can negotiate. As mentioned earlier, this calculation is performed by using (5) if MCS is being used or by (7) together with GBP (Table 2) if m-ISODATA is applied.

Table 4 shows the reserve values calculated in the two proposed cases for all renewable generators. An illustrative example for calculating the reserve with m-ISODATA can be seen in Appendix A.

### 4.3. Results

The reserve values calculated for the wind peers by the m-ISODATA and MCS algorithms are very close. The same occurs for case 2. The biggest difference between them was 1.02 MWh (20.16%), occurred for peer 13 in case 2. For PV peers, the results for case 1 from m-ISODATA and MCS are also close. For case 2, in turn, the biggest difference between them is 1.49 MWh (47.91%) for peer 16. However, despite

**Table 5**
Peers' final dispatch.

| Peer | Consumers | | | | | | | | | | | Producers | | | | | | | | Ext. Grid |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 | 13 | 14 | 15 | 16 | 17 | 18 | 19 | |
| Benchmark solution [MWh] | 3.93 | 10.08 | 6.89 | 0.64 | 3.28 | 4.57 | 1.12 | 0.44 | 0.44 | 2.17 | 2.25 | 47.00 | 7.20 | 3.18 | 3.87 | 6.57 | 0.00 | 0.00 | 0.00 | 26.96 |
| Final energy solution [MWh] | 3.93 | 10.08 | 6.89 | 0.64 | 3.28 | 4.57 | 1.12 | 0.44 | 0.44 | 2.17 | 2.25 | 28.14 | 6.19 | 2.74 | 3.33 | 4.86 | 0.00 | 0.00 | 0.00 | 7.85 |
| Energy plus reserve solution [MWh] | 3.93 | 10.08 | 6.89 | 0.64 | 2.96 | 4.12 | 1,12 | 0.40 | 0.44 | 2.17 | 2.25 | 11.71 | 2.52 | 1.38 | 1.75 | 3.24 | 4.42 | 16.22 | 3.21 | 9.17 |

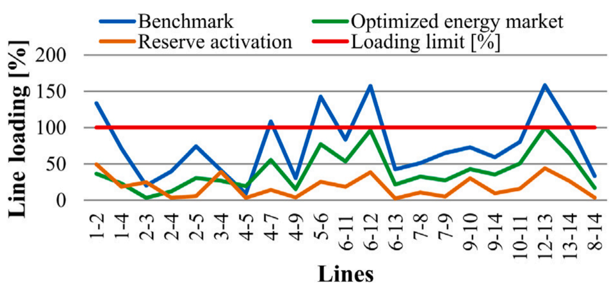


**Fig. 5.** Line-loading for each line [%].

**Table 6**
Economic results.

| Economic parameter | Benchmark solution | Final energy solution | Reserve market solution |
|---|---|---|---|
| Social Welfare [$] | 1595.83 | 1234.48 | 405,66 |
| $\lambda$ [$/MWh] | 23.53 | 26.87 | 16.44 |
| Total traded energy [MWh] | 67.82 | 45.94 | – |
| Total traded reserve [MWh] | – | – | 24.67 |

this difference, the amount in MWh (1.49 MWh) is low, which allows concluding that MCS and m-ISODATA reaches similar results.

To simplify and test the proposed methodology, the renewable peers' reserve values ($R_{min}$ and $R_{max}$) were set as provided in Table 3, by using values calculated using the m-ISODATA clustering algorithm.

To properly analyze the proposed method, a benchmark model is used, which refers to the first step of the first iteration of the proposed model, i.e., the initial P2P market optimization.

Fig. 5 shows the line-loading of the system for the benchmark solution (blue), the final energy market solution (green) and the condition in which all the reserve is activated (orange). One can see that congestion occurs and thus the benchmark solution consists of an unfeasible condition for the network operation. From this initial point, the iterative process reaches a feasible energy market solution after 20 iterations. This result is achieved by applying the PD and limiting the energy supply from generators that cause congestion. Finally, the system's line-loading in the worst case of activating the power reserve is also within the network's operational limits after just 2 iterations. In all the final solutions, there is no violation of the predefined voltage limits. Data from 12 o'clock of one day, chosen randomly from the available data, were used.

The benchmark solution proves the need for a methodology that allows the integration of the DSO with peers to optimize P2P energy and reserve market taking into account network constraints, as there is a high risk of network congestion, since six lines are overloaded in this solution. The proposed approach is able to achieve a solution in which there is no overloaded lines, both for the energy market and for the worst case of reserve activation.

In the benchmark solution, peers trade with each other without regard to PD. Fig. 6 shows the result for the carried out negotiations. In this solution all generators negotiate with all consumers. As there is more renewable generation than demand, the generation surplus is exported to the external grid.

After applying the energy market optimization step of the proposed methodology with PD, the results for trades are shown in Fig. 7. As PD is applied, peers tend to negotiate with their neighbors. It is worth mentioning that a smaller amount of energy is sold to the external grid, since some generators are penalized for having caused congestion in the system's lines.

The negotiations carried out in the reserve market are shown in Fig. 8.

Table 5 shows the peers' final dispatch for the benchmark, final energy solution and energy plus reserve solution. It is observed that both for the benchmark and for the final energy solution, the entire demand of the consumer peers is met (peers 1–11). All the renewable producers (peers 11–16) have a decrease in their dispatched energy. This difference corresponds to a smaller amount of energy negotiated with the external grid, which is required to not violate the network constraints.

For the energy plus reserve solution, three consumers (peers 5, 6 and 8) negotiate their demand flexibility in the reserve market together with the three conventional generators (peers 17–19). Most of the reserve is supplied by these generators.

The energy plus reserve solution corresponds to the case where the entire negotiated reserve needs to be activated. In other words, all the reserve that the renewable peers calculated they might need due to the inherent renewable resources' variability will be necessary, and it is the responsibility of the peers that sold this reserve to provide that energy to the system.

The resulting power flow for the first iteration (benchmark solution) is shown in Fig. 9a. One can see that congestion occurs and thus the benchmark solution consists of an unfeasible condition for the network operation. From this initial point, the iterative process reaches a feasible energy market solution after 20 iterations. This result is achieved by applying the PD and limiting the energy supply from generators that cause congestion (Fig. 9b). Finally, Fig. 9c shows the system's line-loading in the worst case of activating the power reserve. In all the final solutions, there is no violation of the predefined voltage limits.

The economic results from the benchmark, the final energy market and the reserve negotiation are presented in Table 6. The final energy market's social welfare tends to decrease at each iteration, when compared to the benchmark solution, since the proposed method penalizes the bid of the generator that causes congestion, which tends to be among the "cheapest" generators. Thus, another generator, a little more expensive than the previous one, has to be dispatched to make up the difference, causing a decrease in the social welfare or an increase in the market shadow price $\lambda$.

It is noteworthy that despite the decrease in the social welfare, the final energy solution represents a feasible network operating solution, in contrast to the benchmark solution. In a real operating context, the initial transactions could not take place. More precisely, it would require load shedding and, consequently, decrease the total system generation, reaching a feasible operating point that would probably lead to a lower social welfare than that achieved by the proposed approach. It is also worth mentioning that although the proposed methodology has eight steps, the convergence is quite fast, taking only a few seconds.

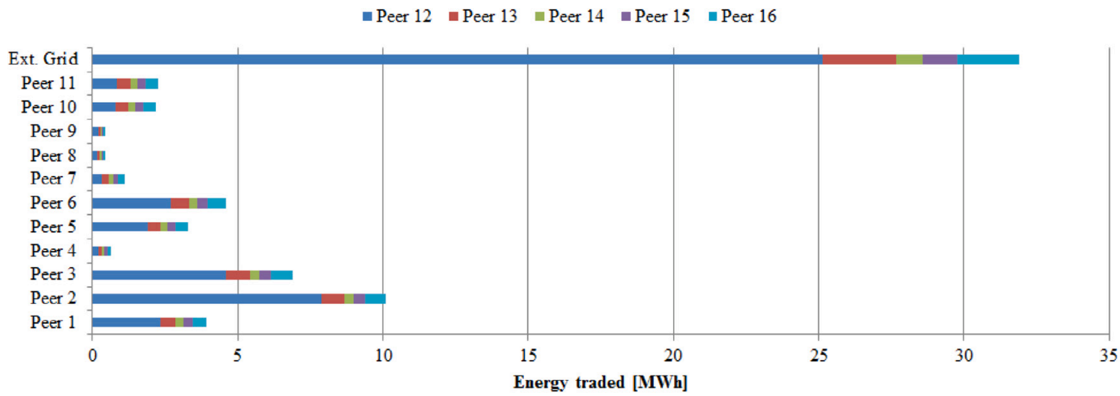


**Fig. 6.** P2P tradings in the benchmark solution. Peers 1–11 and Ext. Grid are energy buyers and peers 12–16 are energy sellers.

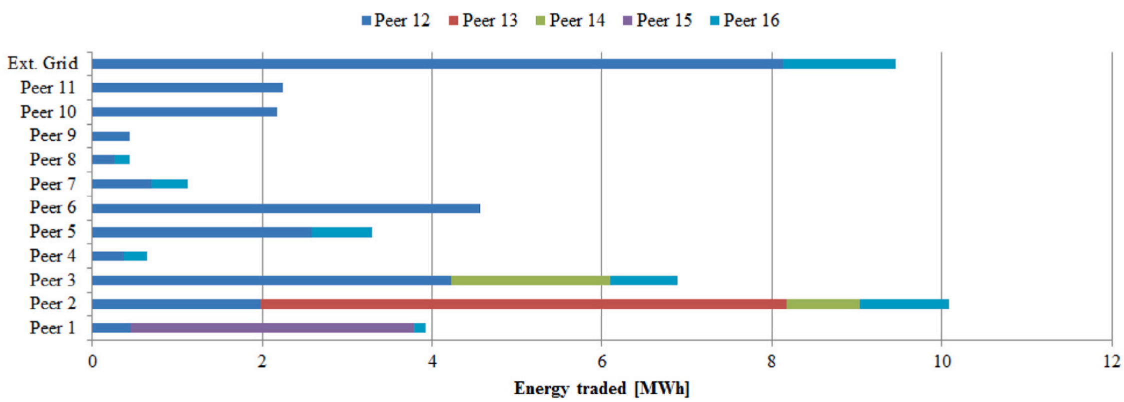


**Fig. 7.** P2P tradings in the final energy market solution. Peers 1–11 and Ext. Grid are energy buyers and peers 12–16 are energy sellers.

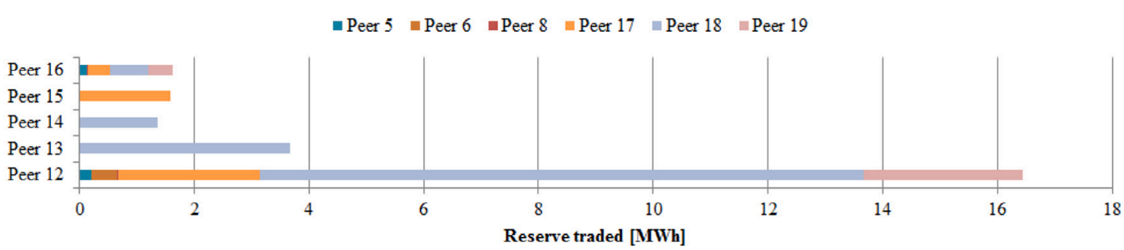


**Fig. 8.** P2P tradings in the final reserve market solution. Peers 12–16 are reserve buyers, and peers 5, 6, 8 and 17–19 are reserve sellers.

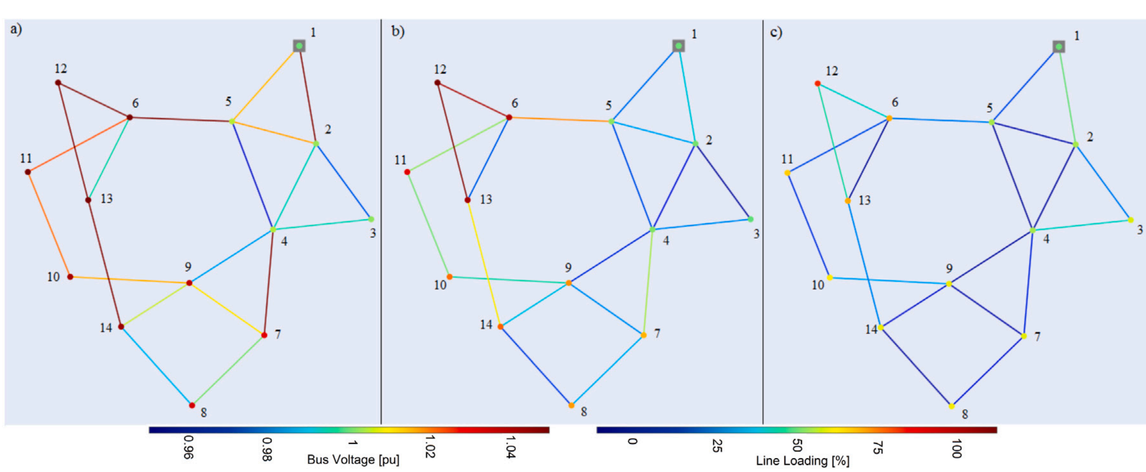


**Fig. 9.** Power flow for the grid. (a) Benchmark solution, (b) Final energy solution, and (c) Worst case of reserve's activation.

## 5. Conclusion

This work proposed an integrated prosumer–DSO approach applied in an iterative sequential approach for energy and reserve P2P market taking into account network constraints, as well as a novel strategy to quantify the reserve required to overcome RES uncertainty. The results obtained for a 14-bus system showed that the proposed methodology is effective to find solutions for the energy and reserve market, while ensuring a feasible network operation and can offer a transition solution to a future more decentralized market environment. Despite the decrease of \$361.35 and the increase of \$3.34 in the market shadow price, the final solution guarantees the feasible operation of the network. Moreover, it is noteworthy there was a decrease of 21.88 MWh in energy negotiations, since it would be operationally unfeasible to use the 67.82 MWh negotiated in the benchmark. The m-ISODATA and MCS algorithm proved to be effective in determining the reserve required by renewable peers. The largest difference between the two algorithms was 1.49 MWh. It can be an alternative for calculating the reserve needed by the system.

Some suggestions for future developments, continuing the line of research described in this paper are: (i) adjust the methodology for joint energy and reserve market design, (ii) use decentralized optimization methods, (iii) explore adequacy of distribution network fees according to the network usage by prosumers, (iv) adapt the proposed methodology from the DSO's perspective and role for a smooth implementation, (v) apply a bigger case study for assessing replicability and scalability, (vi) inclusion of energy storage systems (batteries) and (vii) pursue a more reliable dataset focused on the European market.

## Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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## Appendix A. Example for reserve calculation

*Illustrative example for m-ISODATA:* To obtain the reserve that Peer 12 needs, the data available in the first two columns of Table 2 are used. The total energy negotiated by $E_{12}$ in the P2P energy market is also necessary, i.e., $E_{12} = 28.14$ MWh.

Therefore, from (6) and (7):

$$\begin{aligned}E_{12}^{mISO} = 28.14 \cdot [&(0.0141 \cdot 0.0760) + (0.4483 \cdot 0.0583) + (0.2115 \cdot 0.0711)+\\ &(0.7971 \cdot 0.0660) + (0.1106 \cdot 0.0762) + (0.5913 \cdot 0.0570)+\\ &(0.3213 \cdot 0.0666) + (0.9009 \cdot 0.0718) + (0.0598 \cdot 0.0673)+\\ &(0.5181 \cdot 0.0547) + (0.2651 \cdot 0.0687) + (0.1614 \cdot 0.0735)+\\ &(0.6821 \cdot 0.0646) + (0.3819 \cdot 0.0636) + (0.9652 \cdot 0.0645)] =\\ &11.70 \text{ MWh}\end{aligned}$$

$$R_{12} = 11.70 - 28.14 = \mathbf{-16.44\ MWh}$$

The reserve need for the remaining RES is determined in the same way and presented in Table 4.

**Table B.7**
System data.

| Line | From | To | R | X | B | Size (km) |
|---|---|---|---|---|---|---|
| 1 | 1 | 2 | 0.01938 | 0.05917 | 0.0528 | 4.8738 |
| 2 | 1 | 5 | 0.05403 | 0.22304 | 0.0492 | 3.9278 |
| 3 | 2 | 3 | 0.04699 | 0.19797 | 0.0438 | 2.8833 |
| 4 | 2 | 4 | 0.05811 | 0.17632 | 0.034 | 3.3529 |
| 5 | 2 | 5 | 0.05695 | 0.17388 | 0.0346 | 1.7486 |
| 6 | 3 | 4 | 0.06701 | 0.17103 | 0.0128 | 1.7300 |
| 7 | 4 | 5 | 0.01335 | 0.04211 | 0.45 | 2.8835 |
| 8 | 4 | 7 | 0.000 | 0.20912 | 0.55 | 1.7696 |
| 9 | 4 | 9 | 0.000 | 0.55618 | 0.32 | 2.7540 |
| 10 | 5 | 6 | 0.000 | 0.25202 | 0.45 | 2.5671 |
| 11 | 6 | 11 | 0.09498 | 0.1989 | 0.18 | 1.3472 |
| 12 | 6 | 12 | 0.12291 | 0.25581 | 0.32 | 1.8832 |
| 13 | 6 | 13 | 0.06615 | 0.13027 | 0.32 | 1.9912 |
| 14 | 7 | 8 | 0.000 | 0.17615 | 0.32 | 1.0432 |
| 15 | 7 | 9 | 0.000 | 0.11001 | 0.32 | 1.0000 |
| 16 | 9 | 10 | 0.03181 | 0.0845 | 0.32 | 1.2901 |
| 17 | 9 | 14 | 0.12711 | 0.27038 | 0.32 | 1.8344 |
| 18 | 10 | 11 | 0.08205 | 0.19207 | 0.12 | 1.8044 |
| 19 | 12 | 13 | 0.22092 | 0.1988 | 0.12 | 1.5232 |
| 20 | 13 | 14 | 0.17093 | 0.34802 | 0.12 | 2.6787 |
| 21 | 8 | 14 | 0.17093 | 0.3802 | 0.12 | 4.6787 |

## Appendix B. System data

Table B.7 shows the line data for the 14-bus distribution system, adapted from [53].

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