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A Risk-aware P2P Platform Involving Distributed Generators, Energy Communities and Storage Assets

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Abstract. The decentralization of power systems and networks calls up for a more active participation of end users. In this context, new market and power trading models are arisen. Catalyzed by the evolution of communication infrastructures under the Smart Grid concept, new paradigms such as peer-to-peer (P2P) trading are becoming more common nowadays. This paper develops a P2P platform model, involving the participation of distributed generators (dispatchable and renewable), storage facilities and energy communities. Economic-oriented models are presented for each peer, considering arbitrage capability from storage, generation and flexibility provision. An original market structure is proposed seeking for equilibrium among agents. Moreover, risk-aware operating strategies are developed, which consider adaptive interval formulation of uncertainties. The new approach allows adopting risk-averse or risk-seeker strategies, thus allowing to consider the impact of uncertainties in a flexible fashion. The new platform is tested on a 5-peers case. The impact of demand and renewable penetration on local prices is assessed, concluding that cheap generation contributes to reducing prices and thus improving the economy of users, which can trade energy locally under low prices. Moreover, the impact of uncertainties is also analyzed, observing that the uncertainty level and the risk strategy adopted impact notably on the expected realization of uncertainties. It is also shown that the developed tool effectively seeks for improving the economy of users, even when pessimistic conditions of uncertainties are assumed. Results demonstrate that energy communities are more severely impacted for uncertainties, due to their reduced regulation capability. Finally, the developed tool is further validated in fifty P2P instances from an economic and computational point of view.

Keywords. Distributed generation; Energy community; Peer-to-peer trading; Risk-aware optimization.

Nomenclature

Indices (sets)	
t (I)	Time
i (I)	Energy community
b (B)	Storage facility
g (G)	Distributed generator (dispatchable)
r (R)	Distributed generator (renewable)
$\boldsymbol{\Omega}$	Uncertain parameters
$E[\cdot]$	Expected value of an uncertain parameter
Superscripts	
PV	Photovoltaic generation in communities
D	Inflexible demand
F	Flexible demand
ch/dch	Charging/discharging
U/L	Unserved/dummy power
sa/ps	Spatial arbitrageur/price-setter
$\underline{(\cdot)}/\overline{(\cdot)}$	Minimum/maximum value of a variable or parameter
$\widetilde{(\cdot)}$	Uncertain value
$\widehat{(\cdot)}$	Given value
Parameters	
Θ_i^F	Total flexible energy in the i^{th} community (kWh)
γ_b	Degradation cost for the b^{th} storage facility (€/kWh)
η_b	Efficiency of the b^{th} storage facility (pu)
F_g	Fuel cost of the g^{th} dispatchable generator (€/kWh)
RD_g/ RU_g	Downward/upward ramping limit of the g^{th} dispatchable generator (kW)
ρ	Penalty cost for unserved/dummy power (€/kWh)
M	Large positive constant (-)
ξ	Uncertainty level (-)
$\Delta\omega^l/\Delta\omega^u$	Lower/upper-band of the ω^{th} uncertain parameter (kW)
ϵ	Convergence threshold (-)
Decision variables	
p	Power (kW)
ε	Energy (kWh)
λ	Local price (€/kWh)
ψ	Auxiliary variable to linearize complementarity constraints (binary)
ϕ	Dual variable linked to equality constraints (€/kWh)
$\underline{\mu}/\overline{\mu}$	Dual variable linked to inequality constraints (€/kWh)

1 – Introduction

1.1. – Context and motivation

The power system is evolving towards a more flexible and decentralized paradigm, calling for new businesses, frameworks and management models under the umbrella of the smart grid concept. This paradigm accommodates new agents and technologies, such as prosumers, renewable energy sources (RESs), energy storage or electric vehicles [1]. In this regard, the evolution and modernization of communication technologies enable flexible coordination among agents. In this sense, modern power systems launch market and financial mechanisms looking for a more active participation of all of the stakeholders involved [2].

In this context, peer-to-peer (P2P) platforms, as a way to enable and encourage energy trading among peers, have been demonstrated to boost renewable energy integration and a more flexible and efficient exploitation of local resources [3]. Thereby, P2P trading allows exchanging resources at a much-disaggregated level, thus allowing users and low-scale generators to engage in local markets, paving the way to improve their economy and efficiency [4].

Local markets can be launched within P2P frameworks in order to provide a fair pricing mechanism, which allows to improve the economy of users. Such pricing strategies should be based on equilibrium among users, with the object of clearing prices in a coordinate way seeking for maximizing the collective welfare. However, intermittent behavior of RESs as well as unpredictable local demand suppose major challenges that should be taken into account when designing effective P2P platforms. This paper focuses on this issue.

1.2. – Literature review

Zhang et al [5] propose a local P2P market mechanism to trade both photovoltaic (PV) energy and the risk associated to uncertainties. The designed market arrangement is capable to accommodate forecast errors locally, thus avoiding to propagate them to upward systems. To this end, flexibility provided by local users is harnessed. A decentralized P2P market mechanism is proposed in [6], by which day-ahead energy trading and reserve dispatch are cleared in a coordinated way. By this approach, reserve requirements induced by PV uncertainty are determined under a chance-constrained approach, thus enforcing feasibility under a determined number of uncertainty realization. The proposed framework is solved in a decentralized fashion using the alternating direction of multipliers algorithm. In [7], a decentralized P2P market environment is tailored for multi-microgrids systems. The P2P framework casts as a two-stage clearing mechanism, wherein the first stage deals with individual energy management under uncertainty, whereas P2P trading quantities are negotiated in a decentralized way at the second stage.

In [8], a privacy-preserved algorithm for P2P trading involving buildings is proposed. The proposed algorithm exploits the Benders' decomposition to only exchange boundary information among peers. Overall, the problem casts as a Stackelberg game framework by which the system operator plays as the leader. Rezaei and Ghasemi [9] propose a stochastic-based scheduling tool for multiple energy hubs involving storage systems. The developed tool features robust re-scheduling of local assets and P2P trading in the presence of severe disturbances caused by natural disasters. In this sense, local generators, storage systems and P2P exchanges are exploited in an optimal way with the end of improving the resiliency of the system. Alternatively, the methodology proposed in [10] absorbs uncertainty from renewable generation and demand by employing a short-term forecasting tool using neural networks. Multiple microgrids partake in a P2P platform, which observes the forecast profiles of uncertainties and schedules local assets to minimize the inherent risk.

Mansour Saatloo et al [11], develop a decentralized P2P model for multi-microgrids systems adopting demand response programs. A win-win strategy is proposed casting as an equilibrium model founded on game theory. The developed model is solved in a decentralized fashion using the alternating direction of multipliers whereas uncertainties are modelled using robust optimization. Likewise, the methodology in [12] employs robust optimization to deal with uncertainties in P2P trading involving prosumers. To determine the uncertainty envelopes (i.e. confidence levels), machine learning combined with data-driven approaches are employed. Jia et al [13], develop a P2P trading model for storage assets, renewable generators and flexible loads. Uncertainty trading is enabled for those users owning storage assets or flexible loads. To this end, a game-oriented interval matching approach is developed, by which users follow uncertainty predictions, in order to avoid propagating uncertainty to upstream levels and networks.

A decentralized P2P trading scheme for multi-microgrids systems is developed in [14]. The developed approach employs robust optimization to deal with uncertainties from wind generation. An accelerated alternating direction of multipliers method is employed to solve the problem in a decentralized fashion. In [15], a P2P trading mechanism is proposed for groups of prosumers owning storage systems, PV generators and electric vehicles. Uncertainty in local demand and wholesale prices is managed using Information Gap Decision theory, enabling risk-averse and risk-seeker strategies. Alizadeh et al [16], develop a P2P trading model for multi-carrier systems involving electricity, gas and heating sub-systems. The model seeks for prioritizing P2P trading in order to reduce the imported energy. Multiple uncertainties are modelled through scenarios, while the risk level is controlled by the conditional value at risk metric.

A stochastic capacity planning tool enabling P2P in multi-energy microgrids is developed in [17]. This proposal optimally sizes distributed generators (DGs) while handling uncertainty from renewable sources considering carbon limitations. In [18], a P2P trading model for integrated electricity-heat systems is proposed. The resulting optimization problem is solved in a distributed manner, preserving privacy of users. On the other hand, robustness is ensured by including chance constraints, thus preserving energy balance for a determined realization of uncertainties. Likewise, chance-constrained programming is employed in [19] to cope with uncertainties in P2P trading involving storage, DGs and flexible loads.

Bokopane et al. [20] propose a P2P trading framework for prosumers and charging stations. To this end, a multi-objective optimization model is developed including cost minimization and maximization of renewable use. In [21], a prosumer-centric P2P trading model is proposed. The developed approach considers different types of prosumers which can provide flexibility through optimally scheduling flexible loads. The problem casts as an optimization model solved using Bargaining game theory. Ying et al [22] develop a decentralized P2P trading platform involving different types of buildings. Each building may own rooftop photovoltaic generators or storage assets. The developed platform is solved as a multi-leader, multi-follower, Stackelberg game framework. For the sake of simplicity, Table 1 shows a summary of the studied literature.

1.3 – Research Gaps

The literature review above reveals that existing P2P trading mechanisms under uncertainty mainly feature in the clearing approach considered, agents involved and uncertainty modelling, as summarized in Table 1. A suited clearing mechanism should ensure the maximization of the collective welfare. In other words, the results of the clearing model should be an equilibrium point among peers, thus preserving the willingness of the P2P platform. In this regard, many optimization-based models are performed in a central manner, assuming that a collective agent (e.g. the system operator) has full accessibility to local assets and can manage them. This approach does not ensure the equilibrium reachability since only the objectives of the central agent are taken into account. Other works propose Stackelberg games, in which one agent assumes the role of leader and try to anticipate the response of followers. These frameworks tend to prioritize the objectives of the leader without ensuring the maximization of the rest of utilities [23]. Finally, other approaches may result in complex formulations or heavy algorithms.

Regarding the agents involved, most of the works consider DGs and RESs, while the P2P participation of flexible loads and storage assets is rather infrequent. Whilst, to the best of our knowledge, upcoming agents like energy communities (ECs) have not been explicitly considered in P2P trading yet. In this sense, the existing literature lacks of a proper P2P model involving a variety of peers, including ECs, flexible loads, storage and DGs (renewable and dispatchable).

Table 1 – Summary of the relevant literature

Ref.	**Clearing approach**	**Assets/agents**	**Uncertainty**
[5]	Optimization	RES, FL	Cumulative deviations
[6]	Decentralized consensus	DG, RES	Chance-constrained
[7]	Optimization	DG, RES, ST	Distributionally robust
[8, 22]	Stackelberg	FL, ST	--
[9]	Optimization	DG, ST	Stochastic programming
[10]	Optimization	DG, RES	Short-term forecasting
[11]	Bargaining game	DG, RES, ST	Robust optimization
[12]	Decentralized consensus	RES, FL, ST	Robust optimization
[13]	Bargaining game	RES, FL, ST	Interval notation
[14]	Decentralized consensus	RES, ST	Robust optimization
[15]	Optimization	RES, FL, ST	Information gap
[16]	Bargaining game	RES, FL, ST	Stochastic programming
[17]	Bargaining game	DG, RES	Stochastic programming
[18]	Optimization	DG, RES, ST	Chance-constrained
[19]	Optimization	DG, ST, FL	Chance-constrained
[20]	Optimization	RES, ST	--
[21]	Bargaining game	RES, FL	--
Present	Equilibrium	DG, RES, ST, FL, EC	Interval notation

FL: flexible loads
EC: energy communities
DG: distributed generators
RES: renewable energy sources
ST: storage facilities

Lastly, most of the uncertainty models considered rely on stochastic programming (or chance-constrained), which model the realization of uncertainties via scenarios. Hence, stochastic models present two important drawbacks. On the one hand, the way in which scenarios are generated is critical and not always suited models are available [24]. On the other hand, the resulting optimization problem may be unaffordable if the number of scenarios is large. Few works consider alternative formulations like robust optimization or information gap decision theory. These approaches model uncertainties via intervals and seek for worst or best-case realization of uncertainties, which are not accessible considering stochastic programming, thus resulting in risk-averse or risk-seeker strategies. Moreover, unlike to scenario-based approaches, robust-based approaches are typically adaptive, thus allowing to tune the level of robustness assumed by the operator or coordinator.

1.4 – Specific Contributions

The specific contributions of this work are summarized below:

- Proposing a local P2P trading model including DGs (renewable and dispatchable), storage facilities and ECs involving flexible and inflexible loads. This way, the new proposal includes a number of active agents, thus supposing an invaluable benchmark model for a wide variety of scenarios and layouts.
- Proposing a local market structure based on equilibrium. In this sense, local prices are cleared after solving the first-order optimality conditions of each peer economic model. This particular market arrangement attains for an equilibrium point in the Nash sense, clearing local prices under which P2P trades are performed.
- Developing an uncertainty modelling based on interval notation but, in contrast to other approaches like [25], the proposed model does not cast as a complex min-max optimization framework. Instead, the new proposal solves the problem in an original

iterative way which preserves the linear feature of the optimization model, thus being solvable by average solvers easily.

1.5 – Paper Organization

In the rest of this paper, Section 2 describes the P2P trading platform and states the problem. Section 3 describes the optimization models for the peers involved. Section 4 develops an equilibrium-based solution approach under uncertainty. Section 5 presents a case study with results. Section 6 concludes the paper.

2 – Preliminaries

2.1 – Overview of the considered P2P Platform

Fig. 1 sketches the considered P2P platform as well as the peers involved and main interactions among them. We consider a platform wherein DGs (dispatchable and renewable), ECs and storage facilities engaged in P2P trading. This way, each peer can exchange power with the other stakeholders under local prices (λ). Specifically, ECs can be supplied through DGs and storage facilities, which could provide energy arbitrage by optimally charging-discharging assets. We consider that ECs have also arbitrage capability by optimally managing local flexible loads and distributed renewable generators, including rooftop PV panels mainly [26].

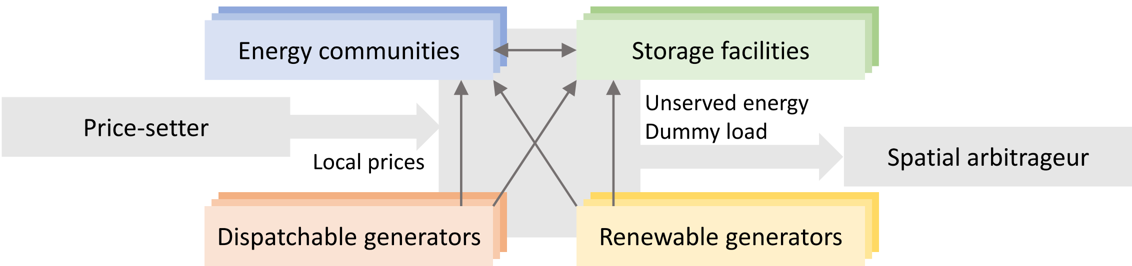

Fig. 1 – Main peers involved in the proposed P2P platform

Such prices are cleared daily by a virtual agent called price-setter. This agent represents a market operator who seeks for reducing the total cost for all the peers in the platform. At the same time, the local prices are revealed in the way that the profit of generators is maximized.

To accommodate the different agents in Fig. 1, we consider an original market structure which aligns with that proposed in [27]. This market arrangement considers the agents in Fig. 1 but also two other agents called spatial arbitrageur and price setter. The spatial arbitrager is a virtual agent, whose role is simply to determine two auxiliary variables, i.e. unserved and dummy power. These two variables ensure the feasibility of results and, in the ideal case, should be equal to zero. On the other hand, the price-setter clears P2P prices under which local energy trading is performed with the objective of maximizing the social welfare. In [27] the authors demonstrated that this market mechanism constitutes a game model, therefore, the solution attained (if exists) constitutes an equilibrium point in the Nash sense.

2.2 – Problem Statement

Let us consider that each peer described above can be modelled via an optimization problem seeking for minimizing energy cost (in case of consumers) or maximizing her own profit (in case of generators). Each peer can be consequently modelled by an objective function and a set of equality and inequality constraints, resulting in the following multi-agent optimization model:

$$\left.\begin{array}{r} \min\limits_{\boldsymbol{x}_i} \mathcal{J}_i \\ \text{s.t.}\, h_i(\boldsymbol{x}_i) = 0\!: \;\; \boldsymbol{\phi}_i \\ g_i(\boldsymbol{x}_i) \le 0\!: \;\; \boldsymbol{\mu}_i \end{array}\right\} \forall i \in I \tag{1a}$$

$$\left.\begin{array}{r}\min_{\boldsymbol{x}_b} \mathcal{J}_b \\ \text{s.t.}\, h_b(\boldsymbol{x}_b) = 0\text{:} \quad \boldsymbol{\phi}_b \\ g_b(\boldsymbol{x}_b) \leq 0\text{:} \quad \boldsymbol{\mu}_b \end{array}\right\} \forall b \in B \tag{1b}$$

$$\left.\begin{array}{r}\min_{\boldsymbol{x}_g} \mathcal{J}_g \\ \text{s.t.}\, h_g\left(\boldsymbol{x}_g\right) = 0\text{:} \quad \boldsymbol{\phi}_g \\ g_g\left(\boldsymbol{x}_g\right) \leq 0\text{:} \quad \boldsymbol{\mu}_g \end{array}\right\} \forall g \in G \tag{1c}$$

$$\left.\begin{array}{r}\min_{\boldsymbol{x}_r} \mathcal{J}_r \\ \text{s.t.}\, h_r(\boldsymbol{x}_r) = 0\text{:} \quad \boldsymbol{\phi}_r \\ g_r(\boldsymbol{x}_r) \leq 0\text{:} \quad \boldsymbol{\mu}_r \end{array}\right\} \forall r \in R \tag{1d}$$

$$\left.\begin{array}{r}\min_{\boldsymbol{x}^{sa}} \mathcal{J}^{sa} \\ \text{s.t.}\, h^{sa}(\boldsymbol{x}^{sa}) = 0\text{:} \quad \boldsymbol{\phi}^{sa} \\ g^{sa}(\boldsymbol{x}^{sa}) \leq 0\text{:} \quad \boldsymbol{\mu}^{sa} \end{array}\right\} \tag{1e}$$

$$\left.\begin{array}{r}\min_{\lambda} \mathcal{J}^{ps} \\ \text{s.t.}\, h^{sa}(\lambda) = 0\text{:} \quad \boldsymbol{\phi}^{ps} \\ g^{sa}(\lambda) \leq 0\text{:} \quad \boldsymbol{\mu}^{ps} \end{array}\right\} \tag{1f}$$

Above, (1a) gathers the problem for each EC in the system, while (1b)-(1d) make similarly for storage facilities, dispatchable generators and RESs, respectively. On the other hand, (1e) and (1f) establish the spatial arbitrageur and price-setter problems, respectively. Note that each peer decides on own variables grouped into vectors $\boldsymbol{x}$, which are detailed in Section 3, while the price-setter decides on local prices. Moreover, each peer modelling may include a set of equality (h) and inequality (g) constraints. In addition, dual variables (the ϕ's and the μ's) are given at the right-hand side of their corresponding constraints.

The problem (1) is not solvable as multiple objective functions (the $\mathcal{J}$'s) must be solved on a whole. To circumvent this issue, each problem in (1) is reduced to its equivalent first-order optimality conditions, resulting in the following mathematical problem with complementarity constraints (MPCC) [27]:

$$\left.\begin{array}{r} h_i(\boldsymbol{x}_i) = 0 \\ k_i(\lambda, \boldsymbol{\phi}_i, \boldsymbol{\mu}_i) = 0 \\ 0 \leq n_i(\boldsymbol{x}_i, \boldsymbol{\mu}_i) \geq 0 \end{array}\right\}; \forall i \in I \tag{2a}$$

$$\left.\begin{array}{r} h_b(\boldsymbol{x}_b) = 0 \\ k_b(\lambda, \boldsymbol{\phi}_b, \boldsymbol{\mu}_b) = 0 \\ 0 \leq n_b(\boldsymbol{x}_b, \boldsymbol{\mu}_b) \geq 0 \end{array}\right\}; \forall b \in B \tag{2b}$$

$$\left.\begin{array}{r} h_g\left(\boldsymbol{x}_g\right) = 0 \\ k_g\left(\lambda, \boldsymbol{\phi}_g, \boldsymbol{\mu}_g\right) = 0 \\ 0 \leq n_g\left(\boldsymbol{x}_g, \boldsymbol{\mu}_g\right) \geq 0 \end{array}\right\}; \forall g \in G \tag{2c}$$

$$\left.\begin{array}{r} h_r(\boldsymbol{x}_r) = 0 \\ k_r(\lambda, \boldsymbol{\phi}_r, \boldsymbol{\mu}_r) = 0 \\ 0 \leq n_r(\boldsymbol{x}_r, \boldsymbol{\mu}_r) \geq 0 \end{array}\right\}; \forall r \in R \tag{2d}$$

$$\left.\begin{array}{r} h^{sa}(\boldsymbol{x}^{sa}) = 0 \\ k^{sa}(\boldsymbol{\phi}^{sa}, \boldsymbol{\mu}^{sa}) = 0 \\ 0 \leq n^{sa}(\boldsymbol{x}^{sa}, \boldsymbol{\mu}^{sa}) \geq 0 \end{array}\right\} \tag{2e}$$

$$\left.\begin{array}{r} h^{ps}(\boldsymbol{x}^{ps}) = 0 \\ k^{ps}(\boldsymbol{\phi}^{ps}, \boldsymbol{\mu}^{ps}) = 0 \\ 0 \leq n^{ps}(\boldsymbol{x}^{ps}, \boldsymbol{\mu}^{ps}) \geq 0 \end{array}\right\} \tag{2f}$$

where stationary (k) and complementarity conditions (n) are included together with the equality constraints in (1) (see [28] for a further explanation).

Note that we only need to assume that each peer modelling in (1) is linear and therefore replaceable by its first-order optimality conditions [29]. (2) constitutes a set of nonlinear equations solvable using a well-suited solver like PATH [30]. However, solving sets of nonlinear equations may entail instability issues [27, 31]. To circumvent such shortcomings, we propose to firstly linearize the nonlinear terms in (2) and secondly include an auxiliary objective function in line with [32], thus transforming (2) into an equivalent linear optimization model.

3 – Mathematical Models of Peers

Subsequent sections present the optimization models representing the strategic behaviour of each peer in the proposed P2P platform. Note that dual variables are shown at the right-hand side of their corresponding constraints.

3.1 – ECs

ECs aim at satisfying local demand at minimum cost, while trading power with other peers via P2P transactions or exploiting local renewable generation through rooftop PV panels. Local demand includes inflexible and flexible loads. The first one must be satisfied instantaneously and correspond to critical loads, while the second one can be deferred but satisfying a minimum energy at the end of the day [31]. Note that this flexible load modelling aligns with features of well-known controllable appliances such as heating-ventilation and air conditioner devices [33]. Under such premises, the EC model writes as:

$$\mathcal{J}_i = \min_{\boldsymbol{x}_i} \sum_{t\in T} \lambda_t p_{i,t} \tag{3a}$$

Subject to:

$$p_{i,t} + p_{i,t}^{PV} - \tilde{p}_{i,t}^{D} - p_{i,t}^{F} = 0: \phi_{i,t}; \forall t \in T \tag{3b}$$

$$\sum_{t\in T} p_{i,t}^{F} - \Theta_i^F = 0: \phi_i^F \tag{3c}$$

$$-\overline{p}_i \leq p_{i,t} \leq \overline{p}_i: \underline{\mu}_{i,t}, \overline{\mu}_{i,t}; \forall t \in T \tag{3d}$$

$$0 \leq p_{i,t}^{PV} \leq \tilde{p}_{i,t}^{PV}: \underline{\mu}_{i,t}^{PV}, \overline{\mu}_{i,t}^{PV}; \forall t \in T \tag{3e}$$

$$0 \leq p_{i,t}^{F} \leq \overline{p}_{i,t}^{F}: \underline{\mu}_{i,t}^{F}, \overline{\mu}_{i,t}^{F}; \forall t \in T \tag{3f}$$

where $\boldsymbol{x}_i = \left[p_{i,t}, p_{i,t}^{PV}, p_{i,t}^{F}\right]$.

The EC objective (3a) minimizes the total energy cost of the community through P2P trading under local prices. Note that the local price is considered a parameter cleared by the price-setter. (3b) establishes power balance in the community accounting for local PV generation, inflexible demand (considered an uncertain parameter) and flexible loads. (3c) establishes a level of flexible energy that needs to be satisfied, in line with the flexible load model in [31]. Note that this amount of energy ensures the correct operation of flexible loads in order to satisfy comfort requirements of users. For example, some types of flexible loads need to be active during some hours through the day and therefore the parameter Θ_i^F ensures this correct operation. Therefore, this parameter should be fixed by the responsible of operating the community according the features of the loads installed in. (3d) binds the power traded with other peers, while (3e) limits the PV generation according to the instantaneous PV potential, considered an uncertain parameter dependent on weather parameters [34]. Finally, (3f) binds flexible power.

It is worth noting that since the local price is considered a parameter in (3), the EC model remains linear and therefore replaceable by its first-order optimality conditions.

3.2 – Storage Facilities

Storage facilities decide on scheduling storage assets aiming at maximize their profit while exchanging energy in the platform, thus resulting in the following optimization problem:

$$\min_{\boldsymbol{x}_b} \mathcal{J}_b = \sum_{t\in T}\{p_{b,t}^{ch}(\lambda_t + \gamma_b\eta_b) + p_{b,t}^{dch}(\gamma_b/\eta_b - \lambda_t)\} \tag{4a}$$

Subject to:

$$\varepsilon_{b,t} - \varepsilon_{b,t-1} - p_{b,t}^{ch}\eta_b + p_{b,t}^{dch}/\eta_b = 0: \phi_{b,t}; \forall t \in T\backslash\{1\} \tag{4b}$$

$$\varepsilon_{b,(t=1)} - p_{b,(t=1)}^{ch}\eta_b + p_{b,(t=1)}^{dch}/\eta_b = 0: \phi_{b,(t=1)} \tag{4c}$$

$$\varepsilon_{b,(t=T)} - \varepsilon_{b,(t=1)} = 0: \phi_b^{end} \tag{4d}$$

$$0 \le \varepsilon_{b,t} \le \overline{\varepsilon}_b: \underline{\mu}_{b,t}^{\varepsilon}, \overline{\mu}_{b,t}^{\varepsilon}; \forall t \in T \tag{4e}$$

$$0 \le p_{b,t}^{ch} \le \overline{p}_b: \underline{\mu}_{b,t}^{ch}, \overline{\mu}_{b,t}^{ch}; \forall t \in T \tag{4f}$$

$$0 \le p_{b,t}^{dch} \le \overline{p}_b: \underline{\mu}_{b,t}^{dch}, \overline{\mu}_{b,t}^{dch}; \forall t \in T \tag{4g}$$

where $\boldsymbol{x}_b = [p_{b,t}^{ch}, p_{b,t}^{dch}, \varepsilon_{b,t}]$.

The objective (4a) represents the total cost of storage facilities, encompassing two terms. First, the cost of trading energy in the P2P platform. Second, we include a degradation cost (γ) as a function of the total energy exchanged, in line with [35, 36]. (4b) establishes the instantaneous state-of-charge (SOC) as a function of the energy traded and efficiency of assets, while (4c) calculates the initial SOC. To avoid storage depletion, (4d) enforces the final SOC to be equal to the initial energy stored. The inequality constraints establish functional limits for the total energy stored (4e), as well as charging (4f) and discharging (4g) power.

Note that the model (4) may accommodate different storage technologies like batteries or hydrogen by simply changing some parameters like the efficiency. As in (3), the local price is considered a parameter in the storage problem and therefore (4) is linear and replaceable by its first-order optimality conditions.

3.3 – Dispatchable Generators

We consider that dispatchable generators are fueled units such as microturbines or fuel-cells. These assets sell energy in the P2P platform aiming at maximizing their expected profit, resulting in the following optimization model:

$$\min_{p_{g,t}} \mathcal{J}_g = \sum_{t\in T} p_{g,t}(F_g - \lambda_t) \tag{5a}$$

Subject to:

$$0 \le p_{g,t} \le \overline{p}_g: \underline{\mu}_{g,t}, \overline{\mu}_{g,t}; \forall t \in T \tag{5b}$$

$$-RD_g \le p_{g,t} - p_{g,t-1} \le RU_g: \underline{\mu}_{g,t}^{R}, \overline{\mu}_{g,t}^{R}; \forall t \in T\backslash\{1\} \tag{5c}$$

The dispatchable generators only decide on the power generated, which is sold at local prices. This way, the objective (5a) represents the profit of the g^{th} generator as the fuel cost given by F_g minus the incomes obtained by trading energy in the P2P platform. On the other hand, (5b) binds the delivered power while (5c) establishes ramping limits, typical features of some technologies like microturbines [37].

Note that since the local price is considered a parameter, (5) is a linear programming model and therefore replaceable by its first-order optimality conditions.

3.4 – Renewable Generators

The proposed model for renewable generators reads as:

$$\min_{p_{r,t}} \mathcal{J}_r = -\sum_{t\in T} \lambda_t p_{r,t} \tag{6a}$$

Subject to:

$$0 \le p_{r,t} \le \tilde{p}_{r,t}: \underline{\mu}_{r,t}, \overline{\mu}_{r,t}; \forall t \in T \tag{6b}$$

As seen, (6) is rather similar to (5) but neglecting ramping limits, assuming that renewable generators have a rapid response. On the other hand, we assume a zero-marginal cost (null fuel cost), in line with other references [38]. Finally, it is worth noting that the upper bound in (6b) is an uncertain parameter representing the instantaneous renewable potential, typically dependent on weather parameters [33]. As the previous models, (6) is a linear programming.

3.5 – Spatial Arbitrageur

Unlike to [27], where the spatial arbitrageur exchanges power with the distribution/transmission system, this agent calculates the unserved energy and dummy load in this paper. These two auxiliary variables are introduced to avoid infeasibility. Indeed, unserved energy may occur when local generation is lower than the total demand, while dummy load could absorb surplus generation to enforce (5c). Particularly, our model aims at maximizing the amount of energy traded through P2P exchanges and therefore the unserved and dummy loads need to be minimized, resulting in the following optimization model:

$$\min_{\boldsymbol{x}^{sa}} \mathcal{J}^{sa} = \sum_{t\in T}\{\rho(p_t^U + p_t^L)\} \tag{7a}$$

Subject to:

$$\sum_{i\in I} p_{i,t} + \sum_{g\in G} p_{g,t} - \sum_{r\in R} p_{r,t} + \sum_{b\in B}\{p_{b,t}^{ch} - p_{b,t}^{dch}\} - p_t^U + p_t^L = 0 : \phi_t^{sa}; \forall t \in T \tag{7b}$$

$$0 \le p_t^U : \underline{\mu}_t^U; \forall t \in T \tag{7c}$$

$$0 \le p_t^L : \underline{\mu}_t^L; \forall t \in T \tag{7d}$$

where $\boldsymbol{x}^{sa} = [p_t^U, p_t^L]$.

The objective (7a) penalizes the amount of unserved energy and dummy load including an artificial cost ρ. This cost should be higher than the maximum generation cost, i.e. $\rho > \max_g F_g$, in order to prioritizes the use of dispatchable generators. Nevertheless, ρ should not be excessively high to avoid numerical instabilities. As a guideline, we observe in our simulations that fixing ρ as the double of the maximum marginal generation cost results in good numerical performance. (7b) establishes power balance in the P2P platform, while (7c) and (7d) bind unserved and dummy energy, respectively, considering A a large positive constant.

3.6 – Price-setter

The price-setter clears local prices in order to minimize/maximize the cost/profit of the peers partaking in the platform, thus giving rise the following optimization model:

$$\min_{\lambda_t} \mathcal{J}^{ps} = \sum_{t\in T}\left\{\begin{matrix}\sum_{i\in I}\lambda_t p_{i,t} + \sum_{g\in G} p_{g,t}\left(F_g - \lambda_t\right) - \sum_{r\in R}\lambda_t p_{r,t} + \\ \sum_{b\in B}\{p_{b,t}^{ch}(\lambda_t + \gamma_b\eta_b) + p_{b,t}^{dch}(\gamma_b/\eta_b - \lambda_t)\}\end{matrix}\right\} \tag{8a}$$

Subject to:

$$\underline{\lambda} \le \lambda_t \le \overline{\lambda} :\ \underline{\mu}_t^{\lambda}, \overline{\mu}_t^{\lambda}; \forall t \in T \tag{8b}$$

The objective (8a) minimize the cost of consumers while maximizing the profit of generators, while (8b) binds local prices. Note that the local price is the unique variable in (8) and therefore the model is linear. Bounds in (8b) can be tuned according to local market rules. For instance, it is typical to set $\underline{\lambda} = 0$, thus avoiding negative prices, while establishing $\overline{\lambda} = \rho$ limits the local price by the highest marginal cost in the platform.

4 – Solution Method

4.1 – Reduction to a MPCC

Each peer represents an optimization problem seeking for improving her economy individually. On the other hand, the actions of each peer needs to be coordinated in order to maximize the collective welfare reaching equilibrium. In present form, the set of optimization problems (3)-(8) cannot be solved directly due to the presence of different objective functions. As discussed in Section 2, each individual problem can be replaced by its equivalent first-order optimality conditions, thus conforming a MPCC as (2), whose solution represents the equilibrium among peers. For simplicity, detailed first-order optimality conditions for each peer are given in the Appendix A.

4.2 – Equivalent Optimization Problem

MPCC frameworks are solvable but its resolution may be challenging due to numerical instabilities arisen from nonlinear complementarity conditions. To solve this issue, we firstly propose to transform the resulting MPCC (2) into an equivalent optimization problem, introducing a dummy objective function [32]. In this paper, the objective of the spatial arbitrageur is selected as the common objective function, thus resulting in the following optimization problem:

$$\arg\min_{\mathbf{X},\mathbf{\Phi},\mathbf{\Pi}} \mathcal{J}^{sa} \tag{9a}$$

Subject to:

$$h_i(\boldsymbol{x}_i, \widehat{\mathbf{\Omega}}) = 0; \forall i \in I \tag{9b}$$
$$h_b(\boldsymbol{x}_b) = 0; \forall b \in B \tag{9c}$$
$$h^{sa}(\boldsymbol{x}_i, \boldsymbol{x}_b, p_{g,t}, p_{r,t}, \boldsymbol{x}^{sa}) = 0 \tag{9d}$$
$$k_i(\lambda_t, \boldsymbol{\phi}_i, \boldsymbol{\mu}_i) = 0; \forall i \in I \tag{9e}$$
$$k_b(\lambda_t, \boldsymbol{\phi}_b, \boldsymbol{\mu}_b) = 0; \forall b \in B \tag{9f}$$
$$k_g(\lambda_t, \boldsymbol{\mu}_g) = 0; \forall g \in G \tag{9g}$$
$$k_r(\lambda_t, \boldsymbol{\mu}_r, \widehat{\mathbf{\Omega}}) = 0; \forall r \in R \tag{9h}$$
$$k^{sa}(\phi_t^{sa}, \boldsymbol{\mu}^{sa}) = 0 \tag{9i}$$
$$k^{ps}(\boldsymbol{x}_i, \boldsymbol{x}_b, p_{g,t}, p_{r,t}, \boldsymbol{\mu}^{ps}) = 0 \tag{9j}$$
$$0 \leq n_i(\boldsymbol{x}_i, \boldsymbol{\mu}_i, \widehat{\mathbf{\Omega}}) \geq 0; \forall i \in I \tag{9k}$$
$$0 \leq n_b(\boldsymbol{x}_b, \boldsymbol{\mu}_b) \geq 0; \forall b \in B \tag{9l}$$
$$0 \leq n_g(p_{g,t}, \boldsymbol{\mu}_g) \geq 0; \forall g \in G \tag{9m}$$
$$0 \leq n_r(p_{r,t}, \boldsymbol{\mu}_r, \widehat{\mathbf{\Omega}}) \geq 0; \forall r \in R \tag{9n}$$
$$0 \leq n^{sa}(\boldsymbol{x}^{sa}, \boldsymbol{\mu}^{sa}) \geq 0 \tag{9o}$$
$$0 \leq n^{sa}(\lambda_t, \boldsymbol{\mu}^{ps}) \geq 0 \tag{9q}$$
$$\mathbf{\Phi}: \text{free} \tag{9r}$$
$$0 \leq \mathbf{\Pi} \tag{9s}$$

where $\boldsymbol{X} = [\boldsymbol{x}_i, \boldsymbol{x}_b, p_{g,t}, p_{r,t}, \boldsymbol{x}^{sa}, \lambda_t]$, $\boldsymbol{\Phi} = [\boldsymbol{\phi}_i, \boldsymbol{\phi}_b, \phi_t^{sa}]$, $\mathbf{\Pi} = [\boldsymbol{\mu}_i, \boldsymbol{\mu}_i, \boldsymbol{\mu}_i, \boldsymbol{\mu}_i, \boldsymbol{\mu}^{sa}, \boldsymbol{\mu}^{ps}]$ and $\mathbf{\Omega} = [\tilde{p}_{i,t}^{D}, \tilde{p}_{i,t}^{PV}, \tilde{p}_{r,t}]$ (see the detailed definition of each vector in the Appendix A).

The optimization problem (9) includes the primal feasibility constraints for ECs (9b), storage facilities (9c) and spatial arbitrageur (9d), while the rest of peers lack of equality constraints in their primal problems and therefore primal feasibility constraints are not included for them. On the other hand, stationary conditions for each peer are given in (9e)-(9j), while (9k)-(9q) are the complementarity conditions. Finally, (9r) and (9s) establish the dual feasibility conditions.

Note that (9) responds to the deterministic clearing of the proposed P2P platform as the vector of uncertainties is considered a given parameter (i.e. $\widehat{\mathbf{\Omega}}$). In this sense, we assume that uncertainties in (9) are parameters and not decision variables, as explained further in Section 4.4.

4.3 – Linearization

Complementarity conditions are nonlinear due to the product of two continuous variables. To linearize them, we employ the well-known big-M approach firstly defined in [39], which establishes that each complementarity condition of the form $0 \leq a \perp b \geq 0$ with $a, b \in \mathbb{R}_+$, can be replaced by the following set of linear constraints:

$$a \leq \psi M \tag{10a}$$
$$b \leq (1-\psi)M \tag{10b}$$
$$\psi \in \{0,1\} \tag{10c}$$

Tuning the big-Ms in economic problems may result challenging and provoke numerical instability [40]. In this paper, we have followed the criteria on [41] to properly tuning the value of the Ms.

4.4 – Risk-aware Resolution

So far, uncertain parameters (gathered in the set $\mathbf{\Omega}$) have been considered parameters given somehow. In this section, we present a risk-aware resolution methodology in order to cope with the effect of uncertainties. To this end, uncertainties need to be declared as decision variables in order to evaluate the risk associated with them. Proper uncertainty modelling is key for risk*aware optimization. In this paper, we employ an interval notation, which is sketched in Fig. 2 and based on declaring the uncertainties as box variables, as follows:

$$E[\omega] - \xi \Delta\omega^l \leq \omega \leq E[\omega] + \xi \Delta\omega^u; \forall \omega \in \mathbf{\Omega} \tag{11}$$

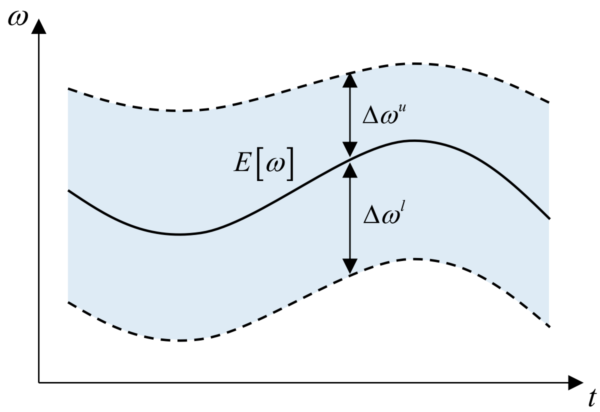

Fig. 2 – Interval notation considered to model uncertainties

It is worth noting that the inclusion of the uncertainty level $0 \leq \xi \leq 1$ makes (11) adaptive. Indeed, the problem becomes deterministic if $\xi = 0$, while all the range of the ω^{th} uncertainty is considered if $\xi = 1$. Note that when $\xi = 0$ the box constraint (11) becomes $E[\omega] \leq \omega \leq E[\omega]$ and therefore uncertainties are enforced to take their expected values.

This particular uncertainty modelling allows adopting risk-averse and risk-seeker strategies. The former adopts a conservative position, assuming that uncertainties will take pessimistic values and therefore its impact is of incrementing the cost of users, while the opposite idea can be applied to the risk-seeker strategy.

To solve the proposed P2P platform under risk-aware strategies, we propose an iterative solution algorithm similar to those proposed in [42, 43]. Firstly, the deterministic problem is solved, as follows:

$$\hat{\lambda}_t, \hat{\boldsymbol{x}}^{sa} \in \arg\min_{\mathbf{X},\mathbf{\Phi},\mathbf{\Pi},\mathbf{\Psi}} \mathcal{J}^{sa} \tag{12a}$$

Subject to:

$$H\left(\mathbf{X}, \widehat{\mathbf{\Omega}}\right) = 0 \tag{12b}$$
$$K\left(\lambda_t, \mathbf{\Phi}, \mathbf{\Pi}, \widehat{\mathbf{\Omega}}\right) = 0 \tag{12c}$$
$$N\left(\lambda_t, \mathbf{X}, \mathbf{\Pi}, \widehat{\mathbf{\Omega}}, \mathbf{\Psi}\right) \leq 0 \tag{12d}$$

$$\mathbf{\Psi} \in \{0,1\} \tag{12e}$$
$$\mathbf{\Phi}: \text{free} \tag{12f}$$
$$0 \leq \mathbf{\Pi} \tag{12g}$$

where $\mathbf{\Psi}$ collects the ψ's of the linearized complementarity constraints (10).

For simplicity, (12b) and (12c) collect all the equality and stationary conditions in (9), while (12d) encompasses the complementarity conditions but linearized following (10), using the binary variables ψ's, properly declared in (12e). Finally, (12f) and (12g) are the dual feasibility conditions.

After solving (12), one obtains local prices under deterministic conditions. As a by-product, primal decision variables of the spatial arbitrageur are also obtained, which are useful for the following stages. It is worth noting that after linearizing the complementarity constraints, (12) is a Mixed-Integer Linear Programming (MILP), solvable by off-the shelf solvers.

After running (12), the coordinator decides whether adopting a risk-averse or risk-seeker strategy. In each case, one needs a utility function reflecting the collective welfare as a function of the uncertainties. In our particular case, the objective of the price-setter effectively reflects the economy of the system and therefore constitutes a suitable objective function for this stage. Thus, the risk-averse problem can be solved, as follows:

$$\widehat{\mathbf{\Omega}} \in \arg\max_{\boldsymbol{X},\mathbf{\Omega}} \mathcal{J}^{ps}(\hat{\lambda}_t) \tag{13a}$$

Subject to:

$$H(\mathbf{X}, \mathbf{\Omega}) = 0 \tag{13b}$$
$$G(\mathbf{X}, \mathbf{\Omega}) \leq 0 \tag{13c}$$
$$E[\omega] - \xi\Delta\omega^l \leq \omega \leq E[\omega] + \xi\Delta\omega^u; \forall \omega \in \mathbf{\Omega} \tag{13d}$$
$$\textstyle\sum_{t\in T} \boldsymbol{x}^{sa} \leq \sum_{t\in T} \widehat{\boldsymbol{x}}^{sa} \tag{13e}$$

where (13c) collects the inequality constraints of primal problems (3)-(6).

The risk-averse strategy aims to maximize/minimize the cost/profit of consumers/generators, establishing an objective contrary to the original P2P model. Thus, by declaring the uncertainties as decision variables, (13) becomes risk-averse and seeks for the worst-case realization of uncertainties, under the box model (13d). Finally, (13e) is included to avoid maximizing the unserved energy leading to unpractical solutions. Similarly, the risk-seeker strategy can be established by just changing the sense of the problem (13) to minimization.

It is worth noting that since local prices are taken as parameters coming from the deterministic problem, (13) is a linear programming (LP). The deterministic and risk-averse/seeker problems are iteratively solved until the difference between two consecutive solutions is marginal, which is measured in our problem as:

$$\left\| \lambda_t^{(j)} - \lambda_t^{(j-1)} \right\|_\infty \leq \epsilon \tag{14}$$

where $\epsilon \in \mathbb{R}_+$ and the superscripts stand for the j^{th} iteration of the algorithm. For the sake of simplicity, Fig. 3 shows a flowchart of the proposed iterative algorithm for risk-aware P2P clearing.

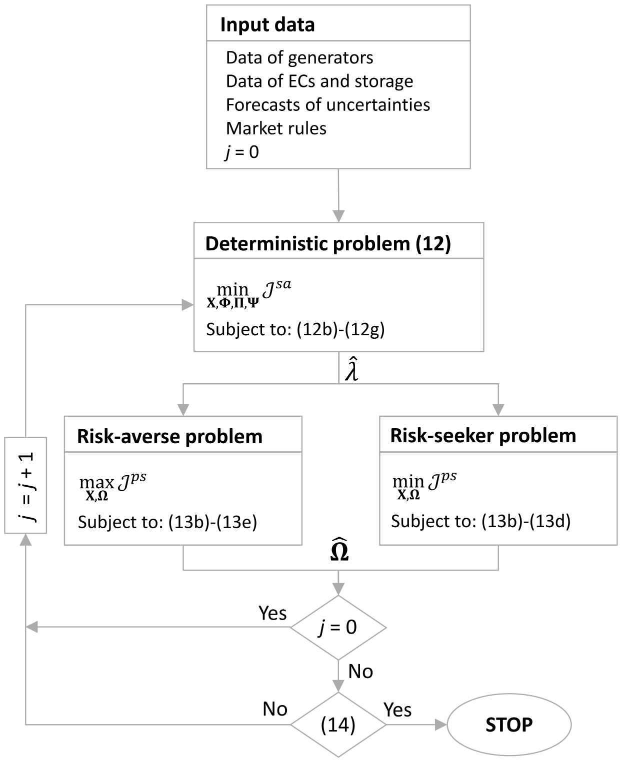

Fig. 3 – Flowchart of the proposed algorithm for risk-aware P2P clearing

As seen in Fig. 3, the developed algorithm requires data of generators and storage, as well as forecasts of uncertainties. The former includes marginal costs, rated powers and maximum capacity in case of storage. Note that these values are considered parameters in the formulation above. Regarding forecasts, they include renewable generation and inflexible demand profiles. These values incorporate into the algorithm as parameters in the deterministic problem, but as variables for the risk-averse and risk-seeker problems.

5 – Case Study

This Section presents a case study with results. We firstly present an illustrative case involving 5 peers. Secondly, the model is further validated for 50 different instances. The developed optimization models were coded under Matlab 2021b and solved using Gurobi [44], on an Intel Core i7-10700K CPU 3.80GHz 3.79 GHz with 32 GB RAM.

5.1 – 5-peers Case

We consider a P2P platform with 5 peers, involving two dispatchable generators, one renewable generator, one storage facility and one EC; whose main data are collected in Tables 2-4. Note that parameters in Table 3 corresponds to a storage asset formed by Li-ion batteries [36]. 24-h profiles for demand and PV potential are plotted in Fig. 2. Note that we have considered PV generators, but other renewable technologies could be perfectly accommodated. Penalty cost for unserved and dummy power was set at 80 €/MWh, considerably higher than the highest fuel cost of dispatchable generators. Finally, local prices are bounded to 0-80 €/MWh.

Table 2 – Data of dispatchable generators data for the 5-peers case

Parameter	**Value**	
	DG #1	**DG #2**
Rated value (kW)	70	30
Fuel cost (€/MWh)	40	20
Upward ramp (kW)	20	10
Downward ramp (kW)	20	10

Table 3 – Data of storage assets for the 5-peers case

Parameter	Value
Rated value (kW)	60
Degradation cost (€/MWh)	2.35
Efficiency (pu)	0.95
Capacity (kWh)	120

Table 4 – Data of EC for the 5-peers case

Parameter	Value
Maximum power (kW)	90
Flexible duty energy (kWh)	313

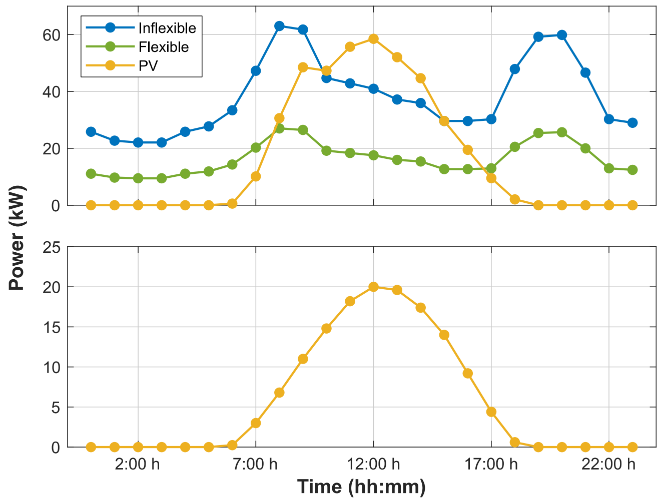

Fig. 4 – 24-h profiles in the 5-peers case. Demand and PV potential for the EC (top) and renewable potential for the renewable generator (bottom)

5.1.1 – Deterministic Case

Firstly, we analyze the deterministic case, which is equivalent to neglect variation of uncertainties (i.e. $\xi = 0$). Fig. 5 plots the scheduling result for this scenario. As observed, the expensive generator (DG #1) is profusely operated at morning, when the EC demand is high, while the joint action of the renewable generation and the cheap DG allows disconnecting the expensive generator for almost all the day. Storage assets leverage central hours of the day for charging through renewable generation, as seen also in Fig. 6. Actually, high renewable potential at midday allows the EC to be self-sufficient. Under such circumstance, dispatchable generators can be disconnected at 10:00 h. Energy stored during midday is discharged at night, when local demand is high. This charging-discharging routine allows disconnecting the expensive generator, which is uniquely operated at 19:00 h and 22:00 h.

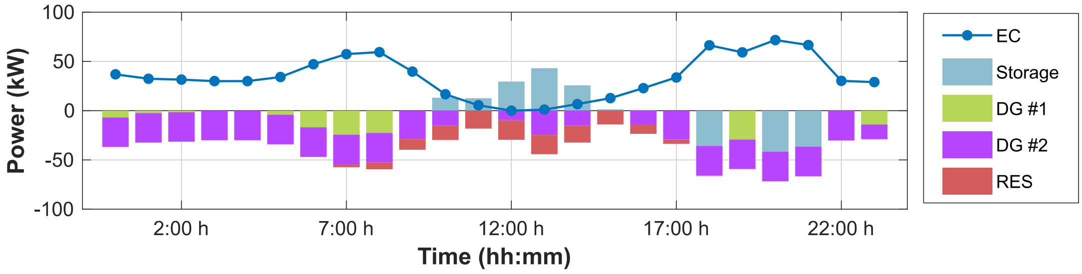

Fig. 5 – Scheduling result for the 5-peers case under deterministic conditions

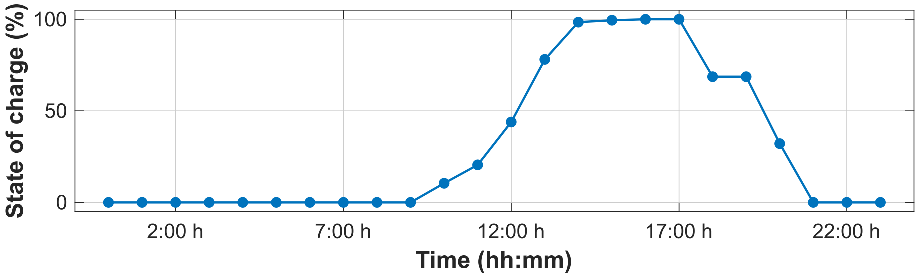

Fig. 6 – State of charge for the 5-peers case under deterministic conditions

Next, we present results for different renewable and demand penetrations. In particular, base profiles in Fig. 4 are multiplied by a real scale factor $\alpha \in \mathbb{R}_+$ in order to asset their impact on final results. Fig. 7 plots the resulting local price for different scale factors. At the top of Fig. 7, the local price for different renewable penetration in ECs is plotted. Not surprisingly, local price is progressively reduced as the value of α grows, but uniquely at midday and afternoon, when PV potential is not null. In particular, with $\alpha = 0$, the local price is almost flat, due to the expensive dispatchable generator needs to be operated almost continuously throughout the day. In this sense, the expensive generator clears the local price being the most expensive generator that needs to be operated. With $\alpha = 1$, local price reduces to 20 €/MWh at midday and afternoon, due to the cheap generator solely supplies the local demand. Finally, local price falls to zero with $\alpha = 2$, this scenario reflects a surplus renewable energy in the EC, allowing to disconnect the dispatchable generators. Note that in the absence of local market, prices from an upscale agent (e.g. retailer) spread through the system and are insensitive to the status of local demand. In this sense, the existence of a local market better reflects the generation cost of the system and eventually allows to reduce costs.

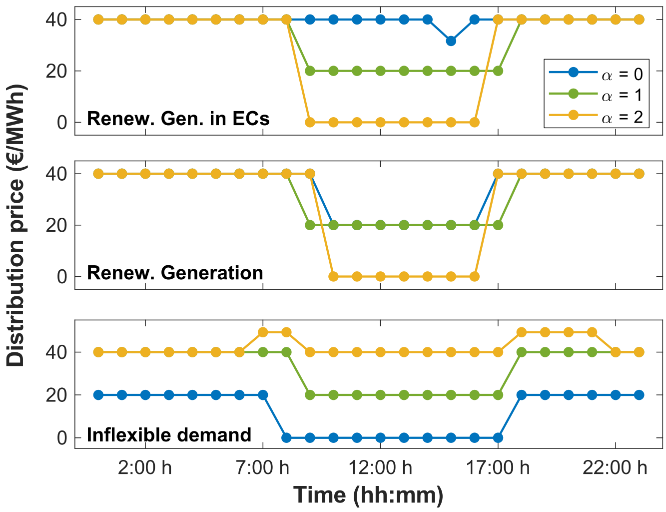

Fig. 7 – Local price for the 5-peers case under deterministic conditions considering different renewable and demand penetrations

In the middle plot of Fig. 7, local prices for different distributed renewable potential are shown. As seen, results in this case are rather similar to those analyzed in Fig. 7 top. However, it is worth noting that local price at midday is still reduced even with $\alpha = 0$, which indicates that local PV generation in the EC has a more notable influence than the distributed renewable generation. This result is coherent, since the renewable potential in the EC is much higher in our case (see Fig. 4). Finally, different demand levels are studied at the bottom of Fig. 7. As expected, the effect of incrementing the demand is contrary to increase the renewable potential. Note that local price is even higher than 40 €/MWh at morning and evening. This effect is due to, at these hours, the system requests the participation of the storage facility through discharging. In the face of this situation, higher prices are cleared in order to compensate degradation costs, which is interesting and can determine the optimal participation of storage assets in the market.

Fig. 8 summarizes the total cost of the P2P platform (objective function of the price-setter) for the different studied scenarios. As seen, the results are coherent with the analysis above. Indeed, total cost is reduced when renewable penetration grows, and increased when the demand grows. It is worth noting that the total cost falls to almost zero when inflexible demand is null ($\alpha = 0$). To better understand this situation, Fig. 9 plots the scheduling result for this case. As seen, under these conditions, dispatchable generators are disconnected for most of the day. Actually, flexible demand is supplied from renewable generators or storage almost completely. In this sense, the total cost comes from the degradation cost of storage assets, which is quantitatively lower than the fuel cost of dispatchable generators.

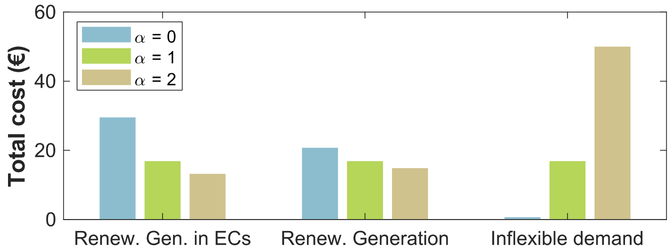

Fig. 8 – Total system cost for the 5-peers case under deterministic conditions, assuming different renewable and demand penetrations

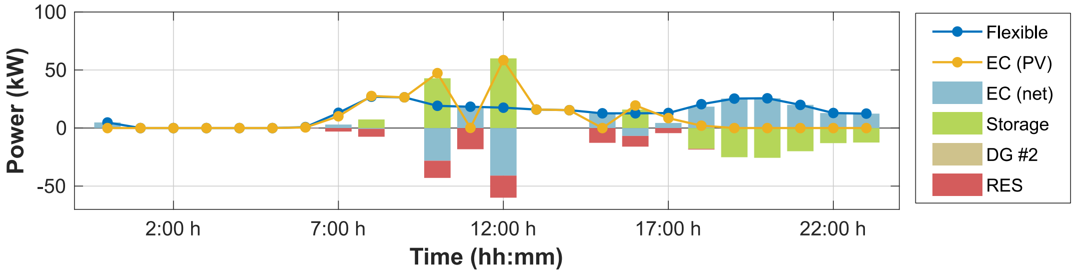

Fig. 9 – Scheduling result for the 5-peers case under deterministic conditions wit null inflexible demand

5.1.2 – Risk-aware Strategies

Next, we analyze the impact of uncertainties on final results. To this end, 25 % confidence intervals are added on benchmark profiles reported in Fig. 4. In particular, we firstly focus on the impact of the uncertainty level on total costs, which constitutes the objective functions of the proposed risk-aware strategies, in Fig. 10. As expected, assuming a risk-aware strategy implies incrementing costs as the uncertainty level increases. This result is coherent since, under this scheduling strategy, pessimistic realization of uncertainties is assumed. Not surprisingly, the total cost decreases when adopting a risk-seeker strategy. To better understand these results, Table 5 summarizes some key results for extreme values of the uncertainty level. As seen in this Table, most of the results are rather coherent, i.e. renewable generation increases under a risk-seeker strategy and decreases for a risk-averse position, while the contrary effect is observed for the demand. However, renewable generation in the EC increases for both risk-aware strategies. This particular behavior is due to renewable generators do not deliver energy for very pessimistic conditions. Under this situation, the algorithm compensates this lack of generation capacity increasing the local generation in the EC. This result demonstrates that the developed methodology is capable to minimize the total cost while assuming pessimistic realization of uncertainties, in line with other similar methodologies [25].

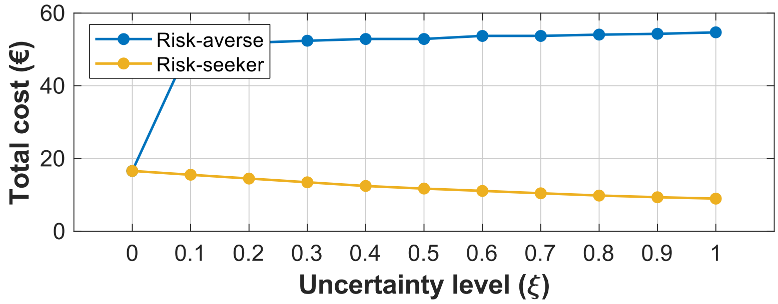

Fig. 10 – Total cost for the 5-peers case for different uncertainty levels

Table 5 – Some results in the 5-peers case for different uncertainty levels

		Risk-averse	Risk-seeker
Renewable generation in EC	$\xi = 0$	408 kWh	408 kWh
	$\xi = 1$	510 kWh	510 kWh
Inflexible demand in EC	$\xi = 0$	915 kWh	915 kWh
	$\xi = 1$	1035 kWh	689 kWh
Renewable distributed generation	$\xi = 0$	139 kWh	139 kWh
	$\xi = 1$	0	174 kWh

In Fig. 11, we focus on the individual cost for each peer under different uncertainty levels and risk-aware strategies. As seen, the EC is undoubtedly more sensitivity to uncertainties than the other peers. This is due to two reasons. Firstly, the EC is directly affected by two sources of uncertainties, i.e. the local demand and PV potential. Secondly, the rest of peers have more regulation capability than the EC, which means that are able to absorb better the impact of uncertainties by adjusting their participation in the market. Indeed, the EC needs to supply local demand regardless the realization of uncertainties, whilst the rest of peers can regulate their participation in the market according the impact of uncertainties and the risk-aware strategy adopted. In this regard, EC partakes in the market actively through flexible demand and local generation, while inflexible demand establishes a passive position of the EC, which is not capable to respond to local prices in an active manner in comparison with the other stakeholders.

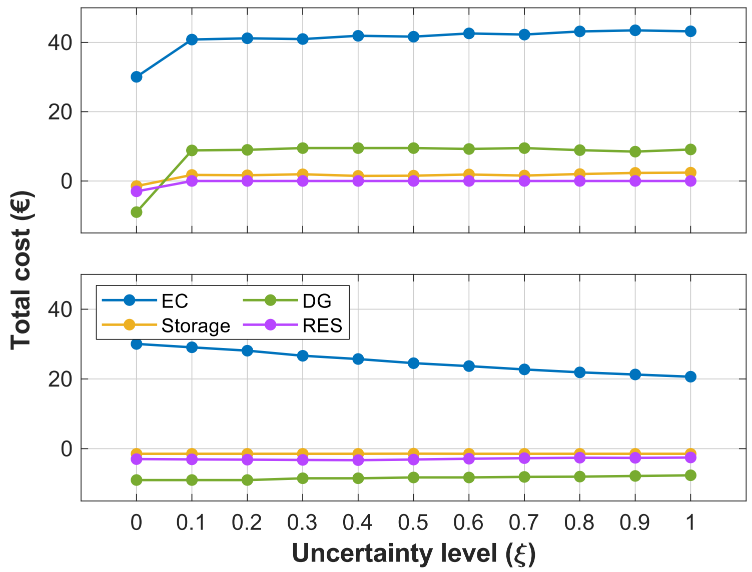

Fig. 11 – Total individual costs for the 5-peers case for different uncertainty levels

5.2 – On the Role of the Price-setter

The price-setter plays a pivotal role on the developed P2P platform. Actually, this agent is responsible of revealing local prices under which local energy trading is performed. To illustrate the performance of this agent, we compare the results obtained with the developed P2P platform with a conventional central dispatching mechanism. In this regard, central dispatching has the objective of reducing the total cost of the platform, i.e. reducing fuel, degradation and unserved energy cost. Results obtained through this approach were similar in both cases, thus demonstrating that the developed approach effectively minimizes the cost of the community.

However, results obtained through central dispatching do not include local prices. In other words, in the absence of the price-setter, local market based on equilibrium cannot be cleared and therefore conventional centralized dispatching mechanisms make inaccessible profit maximization through optimal local prices. Indeed, note that in the absence of local prices, distributed generators and storage facilities cannot obtain a monetary profit by delivering power. This circumstance discourages private investment in distributed assets and corresponds with the conventional paradigm in which a central agent (e.g. the distribution system operator) undertakes investment in network expansion individually. Therefore, these results conclude that the developed approach is capable of effectively reducing the total system cost, but providing local prices as byproduct, which serve to price local energy trading improving the economy of independent agents in consequence, which aligns much better with a modern deregulated distribution system.

5.3 – Other Instances

To further validate the developed tool, up to 50 market instances are built considering the ranges reported in the Appendix B. The different instances were created randomly taking parameters within those ranges, and the total cost in the platform for different uncertainty levels is plotted in Fig. 12. As seen, results in all the instances were coherent and align with the conclusions drawn for the 5-peers case.

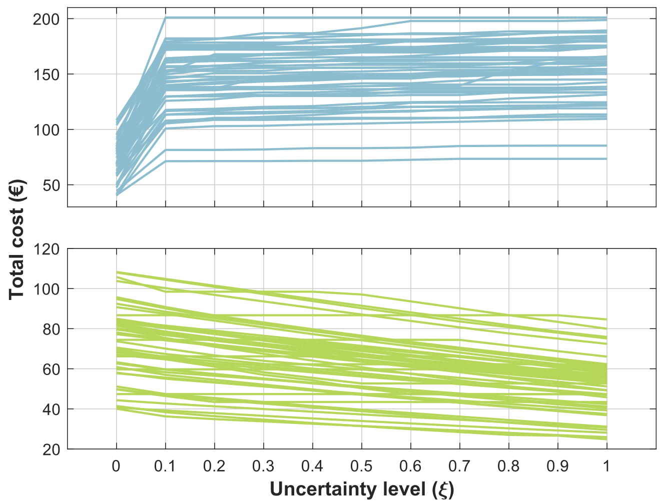

Fig. 12 – Total cost for 50 instances for different uncertainty levels under a risk-averse (top) and a risk-seeker (bottom) strategy

5.4 – Computational Performance

The developed optimization problem iteratively solves a MILP (deterministic problem) and a LP (risk-aware). Both problems are perfectly affordable by off-the-shelf solvers and average machines. Our experiments reveal that the total computational time varies from 15 to 75 seconds, by average, depending on the number of peers involved, mainly. This time burden is perfectly assumable for day-ahead scheduling tools. It is noteworthy that the computational burden overall increases linearly with the number of peers, which demonstrates that the developed tool scales well with the size of the P2P platform.

On the other hand, increasing the uncertainty level expands the solution space, leading to increment the computational time slightly. In this regard, the proposed algorithm typically converges within 2-3 iterations.

5.5 – Comparison with Metaheuristics

As commented above, the developed algorithm solves iteratively a MILP and a LP. Both optimization models could be solved using metaheuristics. In this sense, the experiments performed in this paper were solved using Gurobi, which employs branch-and-bound and interior point algorithms to solve MILP and LP, respectively. These techniques are known to achieve the global optimum effectively and, as commented in Section 5.4, they both are capable to solve the problem effectively.

The scope of this paper is far away to provide an in-depth comparison of the techniques used by Gurobi and different metaheuristics. In this sense, we have performed some preliminary experiments used the metaheuristic proposed in [45]. The results reveal that the metaheuristic is able to achieve the global optimum only in some cases and consuming comparably a large amount of time (above 1000 seconds by average). The solution obtained shows certain variability between consecutive solutions and the quality of results depend notably on input parameters.

In this regard and in line with other authors [46], we consider that exact algorithms (branch and bound) are preferable when the formulation remains linear. In this sense, the developed models are linear and therefore solvable using exact techniques. In conclusion, we recommend uniquely the use of metaheuristics when the formulation is strongly nonlinear or some objective functions are difficult to formulate explicitly.

6 – Concluding Remarks

A novel P2P platform model has been developed in this paper. The new modelling includes economic-oriented models of a variety of agents such as dispatchable and renewable generators, storage facilities and ECs, thus supposing an invaluable benchmark to be used in a variety of layouts and scenarios. Within the developed trading framework and under an original market structure, local prices are revealed seeking for equilibrium among agents, thus improving their economy.

Different risk-aware strategies have been proposed, taking into account the inherent uncertainty of renewable generation and local demand. In this regard, uncertainties have been modelled using an adaptive interval notation. An original iterative solution approach allows solving the model in a risk-aware fashion, preserving the simplicity of the optimization model, thus being solvable by off-the-shelf solvers and average machines efficiently.

The new approach has been tested on a 5-peers case, involving different generators, storage assets and EC. Results validate the model and reveal interesting results. In particular, it is noteworthy that the developed clearing mechanism based on equilibrium allows improving the economy of the different agents. More specifically, energy trading under local prices unlocks economic benefits for distributed generators, which are not accessible in the absence of a local clearing mechanism (price-setter). This improvement of economy and profits, encourage private investments in distributed generators and storage assets, improving the flexibility and efficiency of distribution networks. Also, it has been shown that ECs are more sensitive to uncertainties and are unable to regulate their participation in markets flexibly due to the satisfaction of inflexible demand. Further results validate the adopted risk-aware strategies, demonstrating its effectiveness on providing scheduling results under uncertainties in an adaptive way. Finally, the developed model has been further validated in up to 50 different P2P instances.

In future works, we will apply the results and models developed in this paper to propose novel planning tools, focused on determining the optimal capacity of assets (e.g. renewable generators) taking into account the interaction with other peers in P2P platforms.

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CRediT authorship contribution statement

Marcos Tostado-Véliz: Conceptualization, Methodology, Software, Validation, Formal analysis, Investigation, Data curation, Writing – Original Draft, Writing - Review & Editing, Visualization, Project administration, Funding acquisition. **Seyed Amir Mansouri**: Conceptualization, Methodology, Validation, Formal analysis, Resources, Writing – Original Draft, Writing - Review & Editing, Visualization. **Ahmad Rezaee Jordehi**: Methodology, Validation, Formal analysis, Investigation, Resources, Data curation, Writing - Review & Editing, Supervision. **Salwan Ali Habeeb**: Conceptualization, Data curation, Visualization, Supervision, Project administration. **Francisco Jurado**: Formal analysis, Data Curation, Writing - Review & Editing, Visualization, Supervision, Project administration, Funding acquisition.

Appendix A. First-order Optimality Conditions for Peers

Below, we detail the first-order optimality conditions for each peer, which encompass the primal and dual feasibility, stationary and complementarity conditions (see [28] for a further information).

A.1 – Optimality Conditions for ECs

The first-order optimality conditions for the *i*th community in the platform writes as:

(3b), (3c) (15a)

$$\frac{\partial \mathcal{L}_i}{\partial p_{i,t}} = \lambda_t + \phi_{i,t} - \underline{\mu}_{i,t} + \overline{\mu}_{i,t} = 0; \forall t \in T \quad (15b)$$

$$\frac{\partial \mathcal{L}_i}{\partial p_{i,t}^{PV}} = \phi_{i,t} - \underline{\mu}_{i,t}^{PV} + \overline{\mu}_{i,t}^{PV} = 0; \forall t \in T \quad (15c)$$

$$\frac{\partial \mathcal{L}_i}{\partial p_{i,t}^{F}} = -\phi_{i,t} + \phi_i^F - \underline{\mu}_{i,t}^{F} + \overline{\mu}_{i,t}^{F} = 0; \forall t \in T \quad (15d)$$

$$0 \le p_{i,t} + \overline{p}_i \perp \underline{\mu}_{i,t} \ge 0; \forall t \in T \quad (15e)$$

$$0 \le \overline{p}_i - p_{i,t} \perp \overline{\mu}_{i,t} \ge 0; \forall t \in T \quad (15f)$$

$$0 \le p_{i,t}^{PV} \perp \underline{\mu}_{i,t}^{PV} \ge 0; \forall t \in T \quad (15g)$$

$$0 \le \tilde{p}_{i,t}^{PV} - p_{i,t}^{PV} \perp \overline{\mu}_{i,t}^{PV} \ge 0; \forall t \in T \quad (15h)$$

$$0 \le p_{i,t}^{F} \perp \underline{\mu}_{i,t}^{F} \ge 0; \forall t \in T \quad (15i)$$

$$0 \le \overline{p}_{i,t}^{F} - p_{i,t}^{F} \perp \overline{\mu}_{i,t}^{F} \ge 0; \forall t \in T \quad (15j)$$

$$\boldsymbol{\phi}_i: \text{free} \quad (15k)$$

$$0 \le \boldsymbol{\mu}_i \quad (15l)$$

where $\boldsymbol{\phi}_i = [\phi_{i,t}, \phi_i^F]$, $\boldsymbol{\mu}_i = [\underline{\mu}_{i,t}, \overline{\mu}_{i,t}, \underline{\mu}_{i,t}^{PV}, \overline{\mu}_{i,t}^{PV}, \underline{\mu}_{i,t}^{F}, \overline{\mu}_{i,t}^{F}]$.

Above, (15a) are the primal feasibility constraints, including the equality constraints in (3). (15b)-(15d) are the stationary conditions, resulting from deriving the Lagrangian function of ECs (i.e. $\mathcal{L}_i$) w.r.t. their decision variables. (15e)-(15j) are the conditions linked to inequality constraints in (3). Finally, (15k) and (15l) represent the dual feasibility conditions.

A.2 – Optimality Conditions for Storage Facilities

The first-order optimality conditions for the *b*th storage facility in the platform writes as:

(4b)-(4d) (16a)

$$\frac{\partial \mathcal{L}_b}{\partial \varepsilon_{b,t}} = \phi_{b,t} - \phi_{b,t+1} - \underline{\mu}_{b,t}^{\varepsilon} + \overline{\mu}_{b,t}^{\varepsilon} = 0; \forall t \in T \backslash \{1, T\} \quad (16b)$$

$$\frac{\partial \mathcal{L}_b}{\partial \varepsilon_{b,(t=1)}} = \phi_{b,(t=1)} - \phi_{b,(t=2)} - \phi_b^{end} - \underline{\mu}_{b,(t=1)}^{\varepsilon} + \overline{\mu}_{b,(t=1)}^{\varepsilon} = 0 \tag{16c}$$

$$\frac{\partial \mathcal{L}_b}{\partial \varepsilon_{b,(t=T)}} = \phi_{b,(t=T)} + \phi_b^{end} - \underline{\mu}_{b,(t=T)}^{\varepsilon} + \overline{\mu}_{b,(t=T)}^{\varepsilon} = 0 \tag{16d}$$

$$\frac{\partial \mathcal{L}_b}{\partial p_{b,t}^{ch}} = \lambda_t + \gamma_b \eta_b - \phi_{b,t}\eta_b - \underline{\mu}_{b,t}^{ch} + \overline{\mu}_{b,t}^{ch} = 0; \forall t \in T \tag{16e}$$

$$\frac{\partial \mathcal{L}_b}{\partial p_{b,t}^{dch}} = \gamma_b/\eta_b - \lambda_t + \phi_{b,t}/\eta_b - \underline{\mu}_{b,t}^{dch} + \overline{\mu}_{b,t}^{dch} = 0; \forall t \in T \tag{16f}$$

$$0 \le \varepsilon_{b,t} \perp \underline{\mu}_{b,t}^{\varepsilon} \ge 0; \forall t \in T \tag{16g}$$

$$0 \le \overline{\varepsilon}_b - \varepsilon_{b,t} \perp \overline{\mu}_{b,t}^{\varepsilon} \ge 0; \forall t \in T \tag{16h}$$

$$0 \le p_{b,t}^{ch} \perp \underline{\mu}_{b,t}^{ch} \ge 0; \forall t \in T \tag{16i}$$

$$0 \le \overline{p}_b - p_{b,t}^{ch} \perp \overline{\mu}_{b,t}^{ch} \ge 0; \forall t \in T \tag{16j}$$

$$0 \le p_{b,t}^{dch} \perp \underline{\mu}_{b,t}^{dch} \ge 0; \forall t \in T \tag{16k}$$

$$0 \le \overline{p}_b - p_{b,t}^{dch} \perp \overline{\mu}_{b,t}^{dch} \ge 0; \forall t \in T \tag{16l}$$

$$\boldsymbol{\phi}_b : \text{free} \tag{16m}$$

$$0 \le \boldsymbol{\mu}_b \tag{16n}$$

where $\boldsymbol{\phi}_b = [\phi_{b,t}, \phi_b^{end}]$, $\boldsymbol{\mu}_i = [\underline{\mu}_{b,t}^{\varepsilon}, \overline{\mu}_{b,t}^{\varepsilon}, \underline{\mu}_{b,t}^{ch}, \overline{\mu}_{b,t}^{ch}, \underline{\mu}_{b,t}^{dch}, \overline{\mu}_{b,t}^{dch}]$.

Above, (16a) establishes the primal feasibility constraints, (16b)-(16f) are the stationary conditions, (16g)-(16l) are the complementarity conditions, whereas (16m) and (16n) are the dual feasibility conditions.

A.3 – Optimality Conditions for Dispatchable Generators

The first-order optimality conditions for the g^{th} dispatchable generator in the platform writes as:

$$\frac{\partial \mathcal{L}_g}{\partial p_{g,t}} = F_g - \lambda_t - \underline{\mu}_{g,t} + \overline{\mu}_{g,t} - \underline{\mu}_{g,t}^{R} + \underline{\mu}_{g,t+1}^{R} + \overline{\mu}_{g,t}^{R} - \overline{\mu}_{g,t+1}^{R} = 0; \forall t \in T\backslash\{1, T\} \tag{17a}$$

$$\frac{\partial \mathcal{L}_g}{\partial p_{g,(t=1)}} = F_g - \lambda_{(t=1)} - \underline{\mu}_{g,(t=1)} + \overline{\mu}_{g,(t=1)} + \underline{\mu}_{g,(t=2)}^{R} - \overline{\mu}_{g,(t=2)}^{R} = 0 \tag{17b}$$

$$\frac{\partial \mathcal{L}_g}{\partial p_{g,(t=T)}} = F_g - \lambda_{(t=T)} - \underline{\mu}_{g,(t=T)} + \overline{\mu}_{g,(t=T)} - \underline{\mu}_{g,(t=T)}^{R} + \overline{\mu}_{g,(t=T)}^{R} = 0 \tag{17c}$$

$$0 \le p_{g,t} \perp \underline{\mu}_{g,t} \ge 0; \forall t \in T \tag{17d}$$

$$0 \le \overline{p}_g - p_{g,t} \perp \overline{\mu}_{g,t} \ge 0; \forall t \in T \tag{17e}$$

$$0 \le p_{g,t} - p_{g,t-1} + RD_g \perp \underline{\mu}_{g,t}^{R} \ge 0; \forall t \in T\backslash\{1\} \tag{17f}$$

$$0 \le RU_g - p_{g,t} + p_{g,t-1} \perp \overline{\mu}_{g,t}^{R} \ge 0; \forall t \in T\backslash\{1\} \tag{17g}$$

$$0 \le \boldsymbol{\mu}_g \tag{17h}$$

where $\boldsymbol{\mu}_g = [\underline{\mu}_{g,t}, \overline{\mu}_{g,t}, \underline{\mu}_{g,t}^{R}, \overline{\mu}_{g,t}^{R}]$.

Above, (17a)-(17c) are the stationary conditions, the complementarity conditions gathers in (17d)-(17g) and dual feasibility conditions are given in (17h). Note that primal feasibility conditions are not given as (5) lacks of equality constraints.

A.4 – Optimality Conditions for Renewable Generators

The first-order optimality conditions for the r^{th} renewable generator in the platform writes as:

$$\frac{\partial \mathcal{L}_r}{\partial p_{r,t}} = -\lambda_t - \underline{\mu}_{r,t} + \overline{\mu}_{r,t} = 0; \forall t \in T \tag{18a}$$

$$0 \le p_{r,t} \perp \underline{\mu}_{r,t} \ge 0; \forall t \in T \tag{18b}$$

$$0 \le \tilde{p}_{r,t} - p_{r,t} \perp \overline{\mu}_{r,t} \ge 0; \forall t \in T \tag{18c}$$

$$0 \le \boldsymbol{\mu}_r \tag{18d}$$

where $\boldsymbol{\mu}_r = \left[\underline{\mu}_{r,t}, \overline{\mu}_{r,t}\right]$.

The first-order optimality conditions for renewable generators include the stationary condition (18a), the complementarity conditions (18b) and (18c) as well as the dual feasibility condition (18d). As in (17), primal feasibility conditions are not needed.

A.5 – Optimality Conditions for the Spatial Arbitrageur

The first-order optimality conditions for the spatial arbitrageur writes as:

(7b) (19a)

$$\frac{\partial \mathcal{L}^{sa}}{\partial p_{i,t}^{U}} = \rho + \phi_t^{sa} - \underline{\mu}_t^{U} = 0; \forall t \in T \tag{19b}$$

$$\frac{\partial \mathcal{L}^{sa}}{\partial p_{i,t}^{L}} = \rho - \phi_t^{sa} - \underline{\mu}_t^{L} = 0; \forall t \in T \tag{19c}$$

$$0 \leq p_{i,t}^{U} \perp \underline{\mu}_t^{U} \geq 0; \forall t \in T \tag{19d}$$

$$0 \leq p_t^{L} \perp \underline{\mu}_t^{L} \geq 0; \forall t \in T \tag{19e}$$

$$\phi_t^{sa}: \text{free}; \forall t \in T \tag{19f}$$

$$0 \leq \boldsymbol{\mu}^{sa} \tag{19g}$$

where $\boldsymbol{\mu}^{sa} = \left[\underline{\mu}_t^{U}, \underline{\mu}_t^{L}\right]$.

Above, (19a) is the primal feasibility condition, (19b) and (19c) are the stationary conditions, (19d) and (19e) are the complementarity conditions, (19f) and (19g) are the dual feasibility conditions.

A.6 – Optimality Conditions for the Price-setter

The first-order optimality conditions for the price-setter writes as:

$$\frac{\partial \mathcal{L}^{ps}}{\partial \lambda_t} = \sum_{i\in I} p_{i,t} - \sum_{g\in G} p_{g,t} - \sum_{r\in R} p_{r,t} + \sum_{b\in B}\left\{p_{b,t}^{ch} - p_{b,t}^{dch}\right\} - \underline{\mu}_t^{\lambda} + \overline{\mu}_t^{\lambda} = 0; \forall t \in T \tag{20a}$$

$$0 \leq \lambda_t - \underline{\lambda} \perp \underline{\mu}_t^{\lambda} \geq 0; \forall t \in T \tag{20b}$$

$$0 \leq \overline{\lambda} - \lambda_t \perp \overline{\mu}_t^{\lambda} \geq 0; \forall t \in T \tag{20c}$$

$$0 \leq \boldsymbol{\mu}^{ps} \tag{20d}$$

where $\boldsymbol{\mu}^{ps} = \left[\underline{\mu}_t^{\lambda}, \overline{\mu}_t^{\lambda}\right]$.

Above, (20a) is the stationary condition, (20b) and (20c) represent the complementarity conditions and (20d) is the dual feasibility condition.

Appendix B. Parameters for Instances

Below, the ranges taken for building up the P2P instances considered in simulations are reported.

- Number of players: 5-10
- Peak demand in ECs: 30-70 kW
- Peak renewable generation in ECs = peak demand
- Rated power of storage facilities: 30-90 kWh
- Storage capacity: $2\overline{p}_b$
- Peak power of renewable generators: 10-50 kW

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