A Community-Based Energy Market Design Using Decentralized Decision-Making Under Uncertainty

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***Abstract*—Moving to a user-centric approach is seen as a key change of paradigm in order to increase the efficiency and sustainability of energy systems. Massive integration of new economic agents such as prosumers and mobile or stationary storage will play a key role in the energy transition. In this article, a design of a community-based local energy market (CB-LEM) is proposed where the members are allowed to trade energy among each other through a local pool. The price is set on a day-ahead basis under the coordination of a Community Manager (CM). The novel aspect of this work is that every agent takes part in the determination of the local market price while deciding its own scheduling problem under uncertainty concerning renewable-energy generation and storage. After day-ahead clearing, real time operation and ex-post settlement of the local market by the CM are also explained in order to complete the proposed design. A real case study in a neighborhood in Amsterdam, The Netherlands, is used for testing the proposed framework. In addition, the performance of the ADMM-based clearing process is analyzed in terms of scalability and convergence.**

***Index Terms*—Local energy markets, decentralized decision making, energy community, market clearing.**

NOMENCLATURE

Sets and Indexes

$\mathcal{T}$	Set of periods (index t).
$\mathcal{S}$	Set of scenarios (index s).
$\mathcal{N}$	Set of prosumers (index i).

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Parameters

λ_t^{lem}	Price in the CB-LEM.
$\lambda_{i,t}^{ret,sell}$	Surplus selling price to the retailer.
$\lambda_{i,t}^{ret,buy}$	Buying price from the retailer.
$\overline{E}_i^{ess}$	Energy capacity of ESS.
$\overline{P}_i^{ess}$	Maximum power exchange from storage.
$\underline{SOC_i}$	Minimum state of charge of ESS.
η_{in}	Charging efficiency of ESS.
η_{out}	Discharging efficiency of ESS.
$\hat{d}_{i,t}$,$d_{i,t}$	Forecast and real time demand.
$\hat{pv}_{i,t,s}$	PV generation forecast.
$\overline{P}_i^{grid}$	Maximum power exchanged with the grid.
ω_s	Probability of scenario s.
ρ	Penalty factor in ADMM.
ϵ^p	Primal residual in ADMM.
ϵ^d	Dual residual in ADMM.

Variables

$\hat{P}_{i,t}^{lem}$	Power committed by prosumers in the LEM.
$P_{i,t}^{lem}$	Assigned participation in the LEM.
$\hat{P}_{i,t,s}^{ret}$	Power exchanged with the retailer.
$P_{i,t}^{grid}$	Power actually exchanged with the grid.
$E_{i,t,s}^{ess,out}$	Energy discharged from ESS .
$E_{i,t,s}^{ess,in}$	Energy charging ESS.
$pv_{i,t,s}$	PV generation.

I. INTRODUCTION

A. Motivation and Literature Review

THE INCREASING penetration rates of residential rooftop Photovoltaics (PV) panels as well as other forms of Distributed Energy Resources (DER), such as Electric Vehicles (EV) and Energy Storage Systems (ESS), has led to an increase in the number of prosumers, and opened new market opportunities for different stakeholders in the distribution network. Different self-consumption policies have been adopted to enable prosumers selling their energy back to the grid for a certain price such as Feed-In-Tariffs (FiTs) and net-metering [1]. Such policies had positive effect on the adoption of such technologies. However, at high penetration rates of PV, it would be favorable, both from an economic and technical perspectives, to maximize the utilization of locally produced energy at the demand side. ESS and Demand Side Management (DSM) can improve PV self-consumption and decrease grid imbalance between supply and demand [2]. A more modern approach involves the coordination of prosumers at a community-level where prosumers can trade energy between them. These new market designs are called Local Electricity Markets (LEM), which are typically end-users centered to enhance end-user's choices such as freedom of choice, financial independence and privacy [3]. LEM has attracted researchers' attention in the past few years. This can be recognized in the rise of community-based energy collectives [4], [5].

Different categories of LEM structures can be distinguished in literature depending on the degree of decentralization of the LEM. The main categories are classified into fully Peer to Peer (P2P) and community-based markets [3]. In P2P markets, trades are conducted bilaterally (i.e., prosumers interconnect directly with each other) and there is typically no need for a central operator. One iconic study from the Brooklyn microgrid [6] has implemented a P2P trading scheme in a real physical microgrid. Supply and demand bids in this study are matched using a conventional merit-order dispatch. The work in [7] presents a scheme that enables P2P energy trading without violating low voltage network constraints. The work in [8] proposes an integrated blockchain-based energy management platform for microgrid communities that enables P2P energy trading between prosumers while considering grid constraints. A P2P local electricity market model that incorporates jointly energy trading and uncertainty trading is presented in [9]. The main advantages of such P2P local market designs are maximum independence, freedom, and control of peers over their bilateral trading [3], [8].The second category of LEM structures is energy collectives or community-based markets. In this structure, the interest of the group is paramount, and individual agents may sacrifice some of their own profits and interest for the collective social welfare. In [10], a community-based local market is presented, where the local prices are defined by using premiums indexed to the retailer prices to push the local consumption of energy. A scenario where energy is shared in a microgrid that includes batteries and show benefits for individuals as well as the community as a whole is proposed in [11]. In [12], a cooperative strategy in a community of prosumers to maximize the benefits of each prosumer and the whole community is proposed. The Alternating Direction Method of Multipliers (ADMM) is used to solve the aggregated problem in a decentralized manner. The work in [13] proposes a day-ahead clearing mechanism for an energy community considering grid constraints. In this work, a detailed comparison among centralized and decentralized ADMM-based clearing is also provided. In [14], the two different LEM structures are compared: community-based and P2P. Network constraints are taken into account in both cases. A unified prosumers market formulation is formulated in [15]. This scheme may be operated with both bilateral trades and a centralized pool market, and provides an option for participants to declare preferred trading partners.

Another important field of research deals with the definition of the bidding strategy of the agents participating in the market environment. Both strategic and non-strategic behavior are considered. Thus, In [16], a bi-level bidding strategy for residential prosumers participating in a local energy market is presented. The upper level problem aims at maximizing the profits of a prosumer, while the lower level problem deals with the ESS operation. In [17], a multi-step bidding strategy of autonomous agents under the price-taker assumption that might be used in both wholesale and local energy markets, is presented. In [18], a reinforcement learning algorithm is used to develop bidding strategies for ESSs participating in local energy markets. In [19], a decision tool to be used by small players to optimize their participation in several electricity markets including local energy markets is proposed. In [20], the optimal bidding curve for a set of prosumers is derived. Moreover, a decentralized algorithm is proposed for the distribution system operator to propose a market price that incentivizes the optimal dispatch of the distributed energy resources. In [21], several algorithms are proposed to solve the problem of optimal pricing and scheduling faced by a local trading center managing a set of local sellers and buyers that also interacts with the electrical utility. In [22], a two-stage bidding strategy in a P2P energy market is proposed, splitting energy-related and price-related decisions in two sequential problems. In [23], a mid-market rate based on the ratio generation-demand is proposed in order to define the prices in a P2P energy trading scheme.

Moreover several studies have considered a game-theoretical approach to analyze the strategic interaction among prosumers. A grid-influenced P2P energy trading framework, using a double auction scheme, is proposed in [24]. A cooperative Stackelberg game model is used, in which a centralized power system (i.e., leader of the game) determines the price at peak demand periods, incentivizing neighboring prosumers (i.e., followers) to form coalitions and trade energy locally. A Stackelberg game is formulated in [25] to deal with the problem of optimal trading strategies of uncoordinated P2P energy prosumers. The existence of a unique equilibrium is proven. In [26], an evolutionary game and a Stackelberg game are used to model the interaction among buyers and sellers in a prosumer based community microgrid. A distributed iterative algorithm is proposed to reach the equilibrium states in both games.

B. Research Gap and Contributions

From the review of the research activities concerning local markets summarized in the previous section, a lack of a comprehensive local market design is observed, which should include not only price definition, but also bidding strategy, real-time operation, and final settlement. Moreover, although several approaches have been proposed to define the local market prices on a day-ahead basis, more computationally feasible approaches that explicitly consider uncertainty in the day-ahead market clearing process are needed.

In this article, a community-based local electricity market (CB-LEM) design is proposed, implemented and tested. The main contributions that the study makes are as follows:

- The paper presents a decentralized sequential decision making model as a useful framework for a comprehensive community-based energy market design.

- A scalable, agent-based decomposition strategy is proposed to solve the day-ahead clearing of the CB-LEM, which is modeled as a two-stage stochastic problem in order to explicitly consider uncertainty in each agent's decision making process.
- The real-time decision model of the prosumers is also discussed, and a settlement mechanism to be performed by the community manager is proposed in order to provide a comprehensive market design. The role of the community manager in the LEM is thoroughly defined aiming for a smooth integration of the proposed design within a real-life setting.
- For a realistic assessment of the proposed framework, the optimization model is tested using a data set from an actual prosumer community in the city of Amsterdam, The Netherlands. Moreover, the performance of the clearing process is analyzed in terms of scalability and convergence, using different number of agents, and experimenting with the penalty factor and stopping criteria.

II. Community-Based Local Market Design

The conceptual design of the proposed local market is presented in this section. Each member of the energy community (EC), also sometimes referred to as *agent*, is supposed to have its own contract with a retailer of its choice. Moreover, the agents might own any kind of renewable-based generation assets and/or electricity storage, thus becoming a prosumer in a general sense. A key actor in the proposed framework is the Community Manager (CM). The CM will play the role of local market operator (LMO), including the tasks related with market clearing and settlement. In this work, it is assumed that network losses are so low as to be negligible. The whole decision making problem is split into three sequential subproblems as follows: Day-ahead (D-1 problem), Real-time (RT), and settlement. These subproblems are described in the next subsections, and illustrated in Fig. 1.

A. Day D-1 Problem - Clearing Problem

Day-ahead problem is solved the day before the actual exchanges of energy in the LEM take place. This problem can be cast as a market clearing procedure aimed at defining both an hourly price and the commitments on the amount of energy to be traded by each agent. Several questions arise when defining the clearing problem. On the one hand, the data exchanged for the clearing problem should not compromise the agent's privacy. Moreover, the amount of data exchanged for the clearing should be small in order to reduce the communication burden. On the other hand, agents are asked to commit on the amount of energy to be traded in every hour of the next day which is obviously affected by a certain amount of uncertainty regarding, for example, the actual generation of intermittent renewable generation and demand during day D. In order to tackle these two challenges, a decentralized stochastic clearing mechanism is proposed in this article. Thus, the decentralized approach passes onto the agents most of the computational burden of the clearing process, and the stochastic formulation allows to consider uncertainty in each agent's decision making model.

The setting of the day-ahead problem is as follows. The CM, acting as LMO, coordinates the clearing process. This coordination task implies sending information to the agents, and receiving information back from them. The clearing mechanism thus becomes the result of an iterative process. The CM sends to every member of the community a forecast regarding its PV generation for every hour of day D. This forecast is made up of a set of plausible scenarios and the associated probability of occurrence. Moreover, the CM also sends to each agent the tentative price in the LEM for that iteration. Each agent manages its own data, i.e., electricity demand for day D, and operational data of the ESS, if any. With all these data available, the decision making problem of every agent is modeled as a two stage stochastic problem in order to incorporate the uncertainty regarding PV generation. The first stage decision variables model the commitments in the CB-LEM while the second stage variables deal with scenario dependent variables such as operation of the ESS or the amount of energy traded with the retailer. The decision making of each agent is made independently while a coordinator agent, the CM as LEM operator, is in charge of guaranteeing the CB-LEM clearing. Thus, the commitment of each agent in the CB-LEM after every iteration is sent to the CM. The CM checks if the local market is balanced. If so, the clearing is over. If not, the price is updated and sent back to the agents for another iteration. The agents are assumed to behave rationally, and the iterative and coordinated clearing process does not take into account the strategic behavior of the agents, i.e., each agent's decision model does not consider the possible actions that might be chosen by other agents. The mathematical model of the clearing problem is explained in Section III.

B. Day D - Real Time Problem

For every hour of day D, each agent has to make its actual operational decisions, such as the actual exchange of energy with the grid and the operation of the ESS. All these decisions should be made for every hour but taking into account the commitments already acquired in day D-1 and the available information from that hour on. In this article, a perfect information hypothesis for day D is assumed, i.e., the real time problem can be simplified to a deterministic problem for the whole day D. Defining a policy to decide the RT operation depending on the updated available information in an hourly basis is an interesting research topic which is out of the scope of this work. It should be noted that during RT problem, the agent may decide to not follow its commitments in the CB-LEM. In that case, the agent needs to buy/sell energy from/to the retailer which may be seen as a balancing market. This will be explained in more details in Section III.

C. Settlement

The last stage in the proposed market framework deals with the settlement. From the day-ahead market, the CM knows the commitments of each agent in the CB-LEM. Moreover, the CM has access to the smart meter of each agent, thus knowing

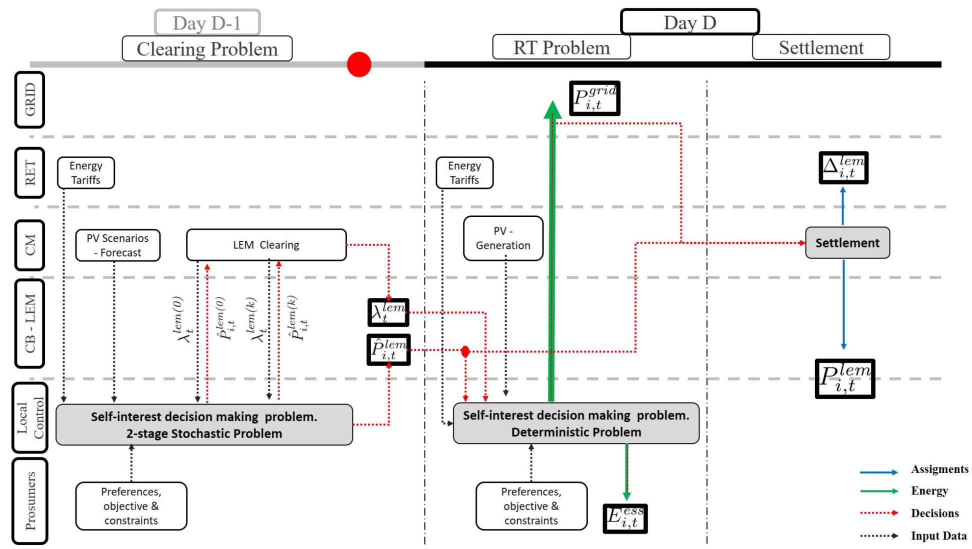


Fig. 1. Sequential Market Framework, showing from left to right, the day-ahead market clearing, real-time and settlement subproblems.

the actual energy exchanged with the grid in every hour of day D. Therefore, the goal of the settlement stage is to reassign the participation on the CB-LEM and the deviations of each agent taking into account the actual behavior of agents in RT. The proposed assignment rules are detailed in Section III.

D. The Community Manager

For this framework to be implementable, the figure of the CM is of paramount importance, and needs to be regulated. Note that the exchanges of energy among the community members are not made behind-the-meter in the proposed setting. Thus, the retailer should not invoice each customer by reading the smart meter directly but after the settlement is done instead. Hence, the CM should be, for example, recognized as a Trusted Third Party (TTP). In this case, the settlement of the CB-LEM would be performed in the first place. Then, the CM can send the results to each retailer in order for them to invoice each agent.

III. Mathematical Model

As described in Section II, the decision making framework is split into three subproblems as follows: clearing, real-time, and settlement. The following subsections translate the aforementioned subproblems into mathematical terms.

A. Day-Ahead Problem - Decentralized Clearing Problem

The clearing problem is solved by the end of day D-1 and aims at setting both a price for the energy exchanged in the CB-LEM for each hour of day D, and the commitments by each member regarding the amount of energy exchanged in every time slot in the LEM. A decentralized clearing problem is proposed. However, a centralized version of this problem is presented in the first place, which is used as the basis to set the decentralized approach. In a centralized approach, the CM, in the role of LEM operator, should have access to all relevant information of each of the members of the community. In such a case, the clearing problem is cast as an optimization problem where the dual variables associated with the energy balancing constraint in the LEM can be interpreted as the clearing prices. A stochastic approach is proposed to handle the uncertainty linked with the PV generation available on day D. In reality, there is also uncertainty regarding the actual demand when solving the day-ahead problem. Without loss of generality, a deterministic demand forecast is assumed in this work. The method can be easily extended to consider scenario-based demand uncertainty, in a similar way as it has been done for PV generation. The objective function defined in equation (1) aims to minimize the weighted cost of the energy supply of all the agents in the community for every scenario modeling the uncertainty in PV generation. The energy prices bought/sold from/to the retailer are known for every agent.

$$\text{minimize} \sum_{s\in\mathcal{S}} \omega_s \sum_{i\in\mathcal{N}} \sum_{t\in\mathcal{T}} \times \left(\lambda_{i,t}^{ret,buy} \cdot \left[\hat{P}_{i,t,s}^{ret}\right]^{-} - \lambda_{i,t}^{ret,sell} \cdot \left[\hat{P}_{i,t,s}^{ret}\right]^{+} \right) \tag{1}$$

where

$$\left[\hat{P}_{i,t,s}^{ret}\right]^{+} = max\left\{\hat{P}_{i,t,s}^{ret}, 0\right\}, \quad \forall i \in \mathcal{N}, \forall t \in \mathcal{T}, \forall s \in \mathcal{S}, \tag{2}$$

$$\left[\hat{P}_{i,t,s}^{ret}\right]^{-} = max\left\{-\hat{P}_{i,t,s}^{ret}, 0\right\}, \quad \forall i \in \mathcal{N}, \forall t \in \mathcal{T}, \forall s \in \mathcal{S}. \tag{3}$$

Equations (2), and (3) are necessary to distinguish between the amount of energy bought from the retailer and the one sold back to the retailer. This distinction is mandatory due to the different prices applying to each transaction. A set of constraints is defined in order to set the operational requirements both at an agent and at community levels.

The amount of PV energy used by *i-th* agent in every time step of day D needs to be smaller than the PV generation available for each scenario, as represented in constraint (4).

$$pv_{i,t,s} \leq \hat{pv}_{i,t,s}, \quad \forall i \in \mathcal{N}, \ \forall t \in \mathcal{T}, \ \forall s \in \mathcal{S}. \tag{4}$$

In every scenario, the operation of the ESS needs to respect a set of operational constraints. This is expressed in a compact form as to expression (5), where $X^{ess}_{i,t,s}$ represents the set of decision variables concerning hourly ESS operation for each agent in each scenario. For example, these decisions include energy charging/discharging or State of Charge (SOC). Moreover, each agent's ESS is characterized by a set of parameters helping to define the corresponding feasible set denoted by Ω^{ess}_i.

$$X^{ess}_{i,t,s} \in \Omega^{ess}_i, \quad \forall i \in \mathcal{N},\ \forall t \in \mathcal{T},\ \forall s \in \mathcal{S}. \tag{5}$$

The feasible set defining the operation of the ESS of each agent, Ω^{ess}_i, is defined by constraints (6)–(11).

$$\begin{aligned} E^{ess}_{i,t,s} = E^{ess}_{i,0} &+ \sum_{\tau=1}^{t} \eta_{in} \cdot E^{ess,in}_{i,\tau,s} \\ &- \sum_{\tau=1}^{t} \frac{1}{\eta_{out}} \cdot E^{ess,out}_{i,\tau,s} \quad \forall i \in \mathcal{N},\ \forall t \in \mathcal{T}, \\ &\forall s \in \mathcal{S}, \end{aligned} \tag{6}$$

$$SOC_{i,t,s} = E^{ess}_{i,t,s}/\overline{E}^{ess}_i \quad \forall i \in \mathcal{N}, \forall t \in \mathcal{T},\ \forall s \in \mathcal{S}, \tag{7}$$

$$\overline{SOC}_i \leq SOC_{i,t,s} \quad \forall i \in \mathcal{N},\ \forall t \in \mathcal{T},\ \forall s \in \mathcal{S}, \tag{8}$$

$$E^{ess}_{i,t,s} \leq \overline{E}^{ess}_i \quad \forall i \in \mathcal{N},\ \forall t \in \mathcal{T},\ \forall s \in \mathcal{S}, \tag{9}$$

$$P^{ess,in}_{i,t,s}, P^{ess,out}_{i,t,s} \leq \overline{P}^{ess}_i \quad \forall i \in \mathcal{N}, \forall t \in \mathcal{T},\ \forall s \in \mathcal{S}, \tag{10}$$

$$E^{ess}_{i,T,s} = E^{ess}_{i,0,s} \quad \forall i \in \mathcal{N},\ \forall s \in \mathcal{S}, \tag{11}$$

The energy balance inside each agent is enforced with constraint (12). This constraint states that the mismatch between PV generation, forecast demand, and charge/discharge of the ESS has to be balanced by exchanging energy with the retailer and with the other agents in the CB-LEM. Each agent has a contract with the DSO which limits the amount of power that can be exchanged through its point of coupling. This is modeled by constraint (13).

$$\begin{aligned} pv_{i,t,s} + E^{ess,out}_{i,t,s} - E^{ess,in}_{i,t,s} - \hat{d}_{i,t} = \hat{P}^{lem}_{i,t} + \hat{P}^{ret}_{i,t,s} \quad &\forall i \in \mathcal{N}, \\ \forall t \in \mathcal{T},\ &\forall s \in \mathcal{S}, \end{aligned} \tag{12}$$

$$\begin{aligned} \left| \hat{P}^{lem}_{i,t} + \hat{P}^{ret}_{i,t,s} \right| \leq \overline{P}^{grid}_i \quad &\forall i \in \mathcal{N},\ \forall t \in \mathcal{T}, \\ &\forall s \in \mathcal{S}. \end{aligned} \tag{13}$$

In order to enforce the clearing of the local market, the commitments of all the agents need to be balanced. This requirement is expressed by the coupling constraint (14). This constraint is enforced in every hour of day D. The dual variable associated with each of these constraints, λ^{centr}_t, may be interpreted as the hourly clearing price in the CB-LEM.

$$\sum_{i \in \mathcal{N}} \hat{P}^{lem}_{i,t} = 0 : \lambda^{centr}_t \quad \forall t \in \mathcal{T}. \tag{14}$$

Thus, the semantics of the centralized clearing problem state that the objective is to minimize the cost of energy supply in the community by allowing an internal exchange of energy among its members. Intuitively, the clearing price in the LEM should be somewhere between the retailer's selling and buying prices. In that foreseeable scenario, each agent would like to participate as much as possible in the LEM, thus reducing its exchange of energy with the retailer, according to (12). However, the individual wishes of each agent are controlled by enforcing the market clearing condition, thus enforcing supply and demand balance in the CB-LEM. The set of constraints of each agent might be either increased in order to add new features such as flexible/deferrable loads or they might be completely different from each other to model heterogeneous communities.

B. Clearing Problem - Decentralized Approach

Let's name Z_i the set of all variables that represent decisions to be made by $i-th$ agent that are part of the coupling constraints. The set of variables that just depend on each agent are summarized on X_i . Thus, the centralized problem can be rewritten as follows:

$$\text{minimize} \ \sum_{i \in \mathcal{N}} f_i(X_i, Z_i) \tag{15}$$

$$\text{subject to} \ X_i, Z_i \in \Omega_i, \tag{16}$$

$$\sum_{i \in \mathcal{N}} Z_i = 0, \tag{17}$$

where $f_i(X_i, Z_i)$ is the objective function (18) of the two-stage stochastic problem that every agent needs to solve in every iteration, and the feasibility set for each agent, Ω_i , is defined by constraints (6)–(13).

$$\text{minimize} \ \sum_{s \in \mathcal{S}} \omega_s \sum_{t \in \mathcal{T}} \left(\lambda^{ret,buy}_{i,t} \cdot \left[\hat{P}^{ret}_{i,t,s} \right]^{-} - \lambda^{ret,sell}_{i,t} \cdot \left[\hat{P}^{ret}_{i,t,s} \right]^{+} \right) \tag{18}$$

The centralized clearing assumes that the LMO has access to all the relevant information of each participant in the CB-LEM. This assumption might not be realistic due to communication burden and privacy concerns. As a consequence, a decentralized model is proposed to clear the local market. More specifically, the aim is to break the centralized problem into N subproblems that can be solved independently by each member of the community. As it can be observed in the centralized model, the clearing problem is separable except for the presence of the balancing constraint which couples the N decision making problems. To handle the coupling constraint, also referred to as complicating constraint, a well-known approach based on the ADMM algorithm is proposed. A comprehensive review of the ADMM algorithm, its origins, and variations is provided in [27]. The objective of this algorithm is to solve the augmented Lagrangian relaxation of the coupling constraint through an iterative and coordinated procedure in order to find an optimal solution of the original problem while providing separability to the problem. When the coupling constraint is a balance equation, as the one in the clearing problem, a particular case of the canonical problem known as the sharing problem is obtained. In this case, the problem can be decomposed by using a simplified version of the ADMM algorithm [27] according to equations (19)–(21). The customization of this algorithm to the clearing problem is as follows. A central coordinator, the CM in our case, broadcast an initial value of the dual variables, i.e., tentative price for the LEM, to every member of the community. Each agent solves its own decision problem,

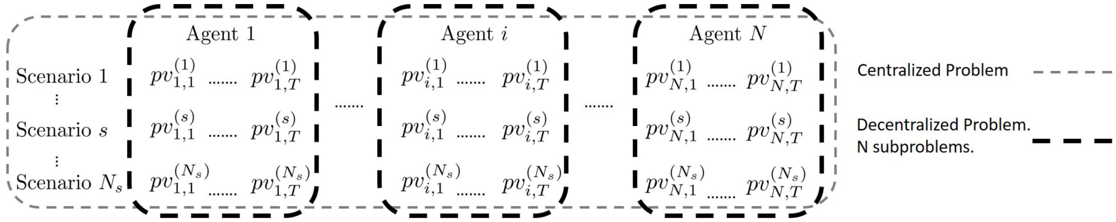


Fig. 2. Decomposition of the centralized problem into a number of subproblems equal to the number of agents.

defined by equations (19) and (20), and sends back to the CM its proposal to participate in the LEM. The central coordinator gather all these tentative commitments and check if the LEM balances. If so, the clearing is finished. If not, the dual variables are updated accordingly, (21), and a new iteration of the clearing is launched. The parameter ρ modules the updating of the LEM prices depending on the average of the individual commitments in each iteration.

Fig. 2 illustrates how the stochastic centralized problem is decomposed in N stochastic decision making problems, each of which is solved independently by each agent.

$$\underset{X_i, Z_i}{\operatorname{argmin}} \; f_i(X_i, Z_i) + \lambda^{T(k)} Z_i + (\rho/2) \left\| Z_i - \left(Z_i^k - \overline{Z}^k \right) \right\|_2^2 \tag{19}$$

$$\text{subject to} \;\; X_i, Z_i \in \Omega_i, \tag{20}$$

$$\lambda^{(k+1)} := \lambda^{(k)} + \rho \overline{Z}^{(k+1)}. \tag{21}$$

The iterative process follows until a convergence criteria is met. A common convergence criteria is for the primal residual to be smaller than a given threshold ϵ^p, as to expression (22)

$$\left\| \sum_{i \in \mathcal{N}} Z_i \right\|_2 \leq \epsilon^p. \tag{22}$$

The dual variables obtained in the decentralized algorithm are guaranteed to converge to the dual values associated to the balance constraint of the centralized problem in the case of convex problems [27]. Given that our decision problem is continuous and convex, this property is the one allowing to clear the proposed CB-LEM in a decentralized setting with optimality guarantees.

C. Day D Problem - Real-Time Problem

At every hour of day D, each agent faces a new decision problem. The actual generation of PV and the actual demand are available, and the agent needs to decide how to operate its assets, mainly the ESS in our case, and the amount of energy to be exchanged with the grid, while taking into account the commitments made in the day-ahead problem. In the ideal case, decisions for a given hour should be made taking into account the uncertain information regarding a set of hours ahead. This can be done, for example, as a sequence of two-stage stochastic problems being the first stage variables those concerning the decisions for the given hour. However, we will consider a deterministic knowledge of hourly PV generation and demand for day D. This (not unrealistic) assumption allows for a simpler implementation because the RT problem can be implemented as a deterministic problem for the whole day D, without compromising the main goal of this article. The decision problem to be solved by each agent in RT is described through equations (23)–(30). The objective function, equation (23), aims at minimizing the cost of energy supply for each agent. The first term is a constant, stating the cost of participating in the LEM. However, this term is kept in the objective function in order to highlight that it is a commitment already acquired in the day-ahead problem. The last two terms represent the cost of buying energy out of the LEM, and the income of selling energy out of the LEM, i.e., from the retailer. This might be interpreted as the retailer acting as a deviation market where the agent can go to buy/sell its deviations with respect to its commitments in the LEM. This means that there exists an implicit penalty because the selling (buying) prices to (from) the retailer are equal or lower (higher) than those in the LEM. An extra penalty may be added in order to further incentivize the agents to develop a more accurate decision making procedure in the day ahead problem. The optimization problem that is solved by every agent $i \in \mathcal{N}$ is formulated as

$$\text{minimize} \; \sum_{t \in \mathcal{T}} \Bigg(-\lambda_t^{lem} \cdot \hat{P}_t^{lem} + \lambda_{i,t}^{ret,buy} \cdot \left[\hat{\Delta}_t^{lem} \right]^- - \lambda_{i,t}^{ret,sell} \cdot \left[\hat{\Delta}_t^{lem} \right]^+ \Bigg) \tag{23}$$

where

$$\hat{\Delta}_t^{lem} = P_t^{grid} - \hat{P}_t^{lem}, \tag{24}$$

$$\left[\hat{\Delta}_t^{lem} \right]^+ = max\left\{ \Delta_t^{lem}, 0 \right\}; \quad \forall t \in \mathcal{T}, \tag{25}$$

$$\left[\hat{\Delta}_t^{lem} \right]^- = max\left\{ -\Delta_t^{lem}, 0 \right\}; \quad \forall t \in \mathcal{T}. \tag{26}$$

The variable Δ_t^{lem}, defined in equation (24), represents the difference between the actual energy exchanged with the grid, i.e., read by the smart meter, and the commitment made in the day ahead clearing process. A positive value means a deviation upwards, i.e., more energy than committed is sold or less energy than committed is bought from the grid. This deviation upwards is valued at the selling retailer price. The same argument is used for deviation downwards. The set of equations (27)–(30) represents the constraints in the RT problem.

$$\text{subject to} \;\; pv_t \leq pv_t^{actual} \quad \forall t \in \mathcal{T}, \tag{27}$$

$$\left| P_t^{grid} \right| \leq \overline{P}_i^{grid} \quad \forall t \in \mathcal{T}, \tag{28}$$

$$pv_t + E_t^{ess,out} - E_t^{ess,in} - d_t = P_t^{grid}, \quad (29)$$
$$X_t^{ess} \in \Omega^{ess}; \quad \forall t \in \mathcal{T}. \quad (30)$$

The decision making problem of each agent in RT is executed in a total selfish mode. It means that it just takes into account its own data and goals. There is no coordination with the rest of the members of the community at this stage at all. After real time operation, a settlement process is needed to perform a final assignment of participation in the CB-LEM.

D. Settlement - Community Manager Model

The CM is in charge of taking care of the final settlement. The settlement is performed with the following available data: commitments in the LEM, prices in the LEM, and actual readings in each prosumer's smart meter. The goal of the settlement process is to assign an actual participation in the LEM to each member, taking into account the actual exchange with the grid in RT, and the commitments acquired in the day-ahead. As a consequence, the actual amount of energy purchased/sold from/to the retailer is also defined. The settlement process is made up of four steps. The first step is aimed at calculating the *responsibility coefficients* of each agent in each time slot. This coefficients represent the relative participation in the deviation upwards or downwards of each agent, as shown by equations (31) and (32).

$$\rho_{i,t}^{up} = \frac{\hat{\Delta}_{i,t}^{lem,up}}{\sum_{i \in \mathcal{N}} \hat{\Delta}_{i,t}^{lem,up}}; \quad \forall t \in \mathcal{T}, \ \forall i \in \mathcal{N}, \quad (31)$$
$$\rho_{i,t}^{down} = \frac{\hat{\Delta}_{i,t}^{lem,down}}{\sum_{i \in \mathcal{N}} \hat{\Delta}_{i,t}^{lem,down}}; \quad \forall t \in \mathcal{T}, \ \forall i \in \mathcal{N}. \quad (32)$$

The next step is to calculate the net power exchange by the community for every time slot. That is the amount of energy that can not be balanced out inside the community in RT, and needs to be exchanged with the grid. Equations (33) to (35).

$$P_t^{net} = \sum_{i \in \mathcal{N}} P_t^{grid}; \qquad \forall t \in \mathcal{T}, \quad (33)$$
$$\left[P_t^{net}\right]^+ = max\left\{P_t^{net}, 0\right\}; \quad \forall t \in \mathcal{T}, \quad (34)$$
$$\left[P_t^{net}\right]^- = max\left\{-P_t^{net}, 0\right\}; \quad \forall t \in \mathcal{T}. \quad (35)$$

The net power calculated in (33) represents the actual deviation that needs to be compensated at the community level. In order to allocate this community deviation among the members, a reassignment of the actual energy exchange in the LEM is done by equation (36). The intuition is to define the actual participation in the LEM as the actual energy exchanged with the grid corrected by the corresponding responsibility of each agent on the net power at the community level. It is to note that all the energy exchanged by an agent deviating from commitments in a different direction than the community as a whole, is assigned as traded in the LEM. Moreover, all the agents benefit from being part of the community at this stage, i.e., in the worst case, each agent needs to compensate for the deviation between the actual exchange in RT and the commitments in the LEM. However, deviations of other agents may reduce the net amount of compensation needed, thus increasing the benefits of participation in the LEM.

$$P_{i,t}^{lem} = P_{i,t}^{grid} - \rho_{i,t}^{up} \cdot \left[P_t^{net}\right]^+ + \rho_{i,t}^{down} \cdot \left[P_t^{net}\right]^-. \quad (36)$$

From an economic point of view, the assigned amount of energy exchanged in the LEM is monetized at the corresponding LEM price defined in the day-ahead market. To complete the settlement process, the amount of energy exchanged by each agent with the grid, that is not assigned by the CM in the LEM, and calculated according to equation (37), needs to be accounted for at the applicable retailer price.

$$\Delta_{i,t}^{lem} = P_{i,t}^{grid} - P_{i,t}^{lem}; \quad \forall t \in \mathcal{T}, \ \forall s \in \mathcal{S}. \quad (37)$$

IV. Numerical Experiments

In this section we present the numerical experiments related to the mathematical models and the algorithms previously described. First we apply the proposed framework over a real case study in a neighborhood of Amsterdam. After that, we analyze the performance of the ADMM algorithm to solve the clearing problem in a decentralized fashion considering a set of instances with different number of agents and several values of the penalty factor.

The simulations were performed within a Python 3.7 environment, using CVXPY [28] to model the subproblems with ECOS [29] as a solver. The computer used for the experiments has a CPU Intel Core i7 10510U 2.30 GHz and 8 GB of RAM.

A. Case Study

A case study of a residential neighborhood in the city of Amsterdam, The Netherlands, is used as an actual case for the testing of the developed framework. Data of ten households from the neighborhood is used for running the simulation over one day. All those households are prosumers with a PV capacity between 2-5 kWp and all own a local ESS of 10 kWh. Firstly, the clearing problem is executed in a day-ahead basis, i.e., day D-1. The CM sends to each member of the community the available forecast for the anticipated hourly PV generation as a set of plausible scenarios. In particular, three PV generation scenarios are used in this case study, however, given the decentralized approach, a higher number of scenarios could be proposed without compromising the computational tractability of the model. Moreover, an initial tentative price for the energy traded in the LEM is also broadcast to all the members of the community. The energy price in the LEM should be somewhere between the selling and purchasing retailer prices. Thus, the initial price in the LEM is proposed as the average of the retailer prices. The iterative process to solve the clearing problem is shown in Fig. 3. In the left subfigure, the sequence of tentative LEM prices for every hour of day D is shown. The case study is run in a relatively small and homogeneous setting. Thus, the prices in the LEM behave in a quite expected way, being lower during the hours when more PV generation is available. In the bottom right subfigure, the considered scenarios for PV generation available for all the agents are shown. Moreover, the forecast demand for a given agent

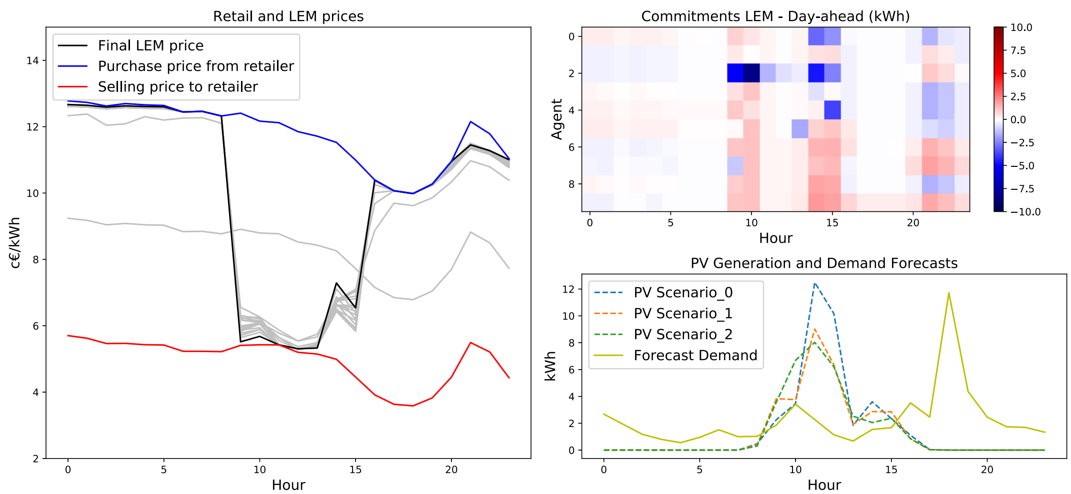


Fig. 3. Day Ahead Problem. Left: Hourly prices in the LEM. Upper right: Hourly commitments of each agent in the LEM. Bottom right: Data available regarding PV generation and Demand for day D.

is also shown. This pattern is common in residential settings, there being a temporal gap between peak generation available and peak demand. This situation is reflected in the prices in the LEM as seen in the left subfigure in Fig. 3. The clearing problem also aims at defining the commitments regarding the amount of energy to be traded in the LEM. This is shown in the upper right subfigure. It is observed that the more energy is exchanged in the LEM the lower the prices are, and vice versa. Secondly, during the RT problem, each agent optimizes its own operational decisions taking into account the actual PV generation available, and its actual demand. These decisions mainly include the operation of the ESS and the actual energy exchange with the grid. To make these decisions, each agent takes into account both the price of energy and its own commitments in the LEM. In Fig. 4 the case for a given agent is shown. In this case, it is worth highlighting how this agent not just charges the ESS during PV generation peak hours, but also discharges the ESS during those hours to fulfill the commitment in the LEM. Lastly, the CM is in charge of the market settlement, i.e., of performing a final assignment of participation in the LEM for each member of the community, taking into account their commitments in day D-1 and their actual amount of energy exchanged in RT. Fig. 5 shows the settlement process for a given hour of day D. In particular, at the analyzed hour, the community as a whole injects into the grid almost 12 kWh. From the upper left figure, it is observed that Agent 3 is fully respecting its commitments in LEM. Moreover, Agent 1 and Agent 5 are deviating downwards from their commitments, by 0.05 and 1 kWh respectively. As a consequence, as shown in the bottom left subfigure, these three agents are assigned a participation in the LEM matching its actual exchange of energy in RT. Conversely, all the other agents are deviating upwards in RT. These agents are in charge of sharing the net energy exchange as a function of the defined coefficients of responsibility. Accordingly, they are assigned a participation in the LEM. It can be observed how the agents deviating opposite to the community as a whole are not penalized; this is because the rest of the members also benefit from that fact, increasing

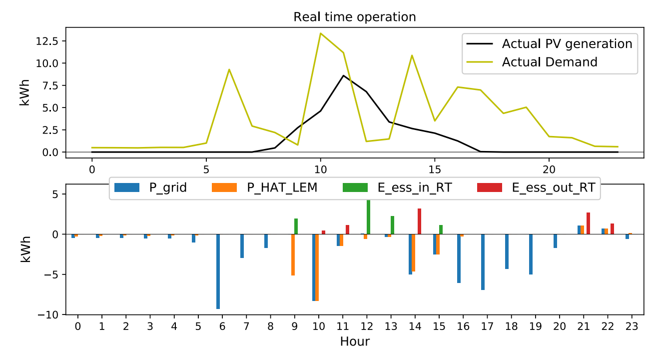


Fig. 4. Real Time operation decisions of a given agent.

the amount of energy that is traded locally, i.e., decreasing the net energy exchanged with the grid.

B. Analysis of the ADMM Algorithm Performance

In this subsection we aim to analyze the performance of the ADMM algorithm in solving the day-ahead clearing problem, especially regarding its scalability and the influence of the penalty factor. As mentioned earlier, the application of this algorithm allows to decompose the centralized problem by individual agents, thus ensuring the scalability of the proposed framework. In this way, at each iteration of the algorithm, each agent has to solve its own subproblem. For this reason, it is worthwhile to study the computational behavior of the algorithm depending on the number of agents. For testing the algorithm, we consider 5 instances with a different number of agents: 10, 20, 40, 80 and 100. The first instance corresponds to the data of the case study of the previous subsection.

Moreover, as it is well known, the performance of the ADMM algorithm is extremely sensitive to the choice of the penalty parameter ρ. In a recent work [30], the authors proposed an ADMM algorithm for two-stage stochastic programming problems, and they provide some numerical evidence that, for such problems, values of ρ between $\frac{1}{|\mathcal{S}|}$ and

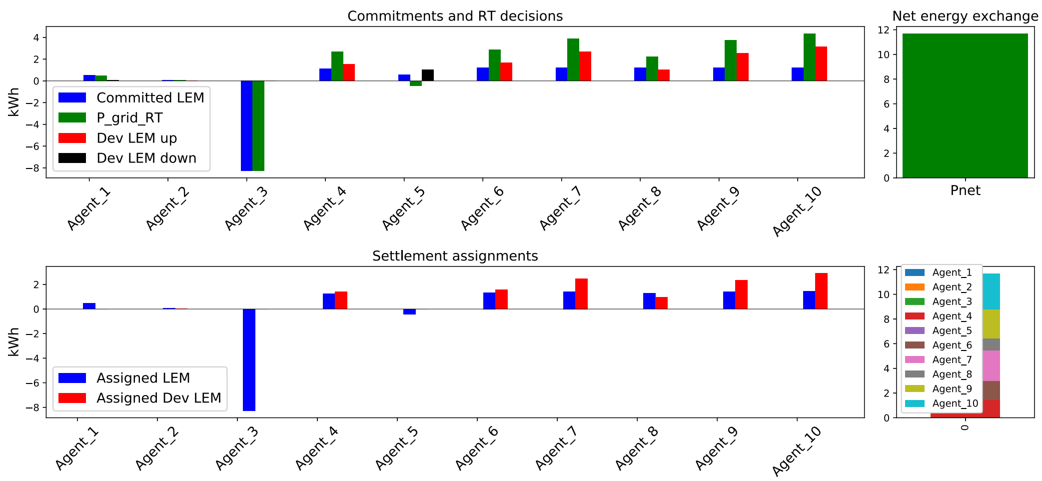


Fig. 5. Settlement Problem. Top left: Inputs to the settlement process. Bottom left: Assignment of participation in the LEM. Top right: Net energy exchange between the community and the grid. Bottom right: Assignment of the net energy exchanged with the grid at the community level to each agent.

$\frac{1}{\sqrt{|\mathcal{S}|}}$ lead to stable results, where $|\mathcal{S}|$ is the number of scenarios considered. We present a similar analysis with our problem, but taking into account that in our case the decomposition is done by agents instead of by scenarios. This approach also allows to link both issues, expressing the penalty factor as a function of the number of agents. In detail, for each instance, we run the algorithm for five values of the penalty factor ρ (depending on the number of agents of the instance), namely: $\rho = \frac{1}{|\mathcal{N}|}$, $\rho = \frac{1}{\sqrt{|\mathcal{N}|}}$, $\rho = 1$, $\rho = \frac{|\mathcal{N}|}{2}$ and $\rho = |\mathcal{N}|$.

We run the algorithm until the primal residual verifies equation (22) with $\epsilon^p = 10^{-3}$, or a maximum number of iterations of 200 is reached. Note that the considered condition over the primal residual can be expressed in terms of the original variables as follows:

$$\left\| \left(\sum_{i \in \mathcal{N}} \hat{P}^{lem}_{i,t} \right)_{t \in \mathcal{T}} \right\|_2 \leq \epsilon^p = 10^{-3} \tag{38}$$

Fig. 6(g) presents for each of the instances with different number of agents, the evolution along the iterations of the objective value given in equation (18) (in first row) and the primal residual (with a zoom) for the different values of ρ (in second row). For the sake of space, we do not present the plots related to instances with 20 and 80 agents because they showed similar behavior to those of 10 and 100 agents, respectively. The overall results and the solutions obtained in all experiments, using the stopping criteria in (38), are presented in Table I.

As it can be observed, the behavior of the algorithm for the instances with 10, 20 and 40 agents, is quite similar. The ADMM algorithm will converge to a similar objective value for all values of ρ. Regarding the convergence, the higher the value of ρ, the faster the primal residual decreases to the threshold. However, observing in Fig. 6(g) the zoom of the primal residual, this does not mean that the higher values of ρ reach faster the stopping criteria over the primal residual. The value of $\rho = \frac{1}{|\mathcal{N}|}$ seems to be too small, since it is not able to enforce primal residual convergence for any instance (i.e., reaching the maximum number of iterations of 200) except for 10 agents. The case of $\rho = 1$ shows the best performance among the three instances, since it yields the fastest convergence, requiring, respectively, 36, 64 and 107 iterations to converge.

For the instances with 80 and 100 agents, we observe quite a different behavior. Regarding the objective value, while the choices of $\rho = 1$ and $\rho = \frac{1}{\sqrt{|\mathcal{N}|}}$ seem to converge to similar objective values (see Table I), the other choices converge to different ones. This is due to the fact that $\rho = \frac{1}{|\mathcal{N}|}$ has a very small value for these instances so there is not enough emphasis on feasibility (see the evolution of the primal residual in Figure 6(g)). On the other hand, $\rho = \frac{\mathcal{N}}{2}$ and $\rho = \mathcal{N}$ take a too large value, so they do not put emphasis on minimizing the original objective function (18). The table also shows that in the case with 80 and 100 agents, the algorithm does not converge for any value of ρ. It is very important to emphasize

TABLE I
Objective Values, Primal Residuals, Dual Convergence and Number of Iterations Under Stopping Criteria $\epsilon^p = 10^{-3}$

Instance ($\lvert\mathcal{N}\rvert$)	$\rho(\lvert\mathcal{N}\rvert)$	Objective Value	Primal	Dual	Iterations
	0.10	1627.69	0.0010	0.0013	99
	0.32	1627.71	0.0003	0.0000	51
10	1.00	1627.71	0.0007	0.0004	36
	5.00	1627.91	0.0007	0.0009	61
	10.00	1628.17	0.0007	0.0013	75
	0.05	2950.06	2.1337	0.0053	200
	0.22	2972.23	0.0007	0.0000	65
20	1.00	2972.27	0.0003	0.0001	64
	10.00	2974.77	0.0007	0.0008	150
	20.00	2983.81	0.0005	0.0014	116
	0.03	1370.71	5.6734	0.0035	200
	0.16	1440.38	0.4676	0.0018	200
40	1.00	1449.70	0.0006	0.0001	107
	20.00	1464.43	0.0005	0.0024	168
	40.00	1474.20	0.0073	0.0087	200
	0.01	-5343.73	252.1029	0.0394	200
	0.11	3597.33	1.6777	0.0023	200
80	1.00	3629.72	0.2965	0.0041	200
	40.00	4349.62	0.0422	0.0262	200
	80.00	4847.24	0.0573	0.0731	200
	0.01	-14210.46	317.4238	0.0320	200
	0.10	-2268.32	0.3178	0.0003	200
100	1.00	-2262.65	0.0601	0.0005	200
	50.00	-1468.68	0.0520	0.0337	200
	100.00	-838.29	0.0330	0.0388	200

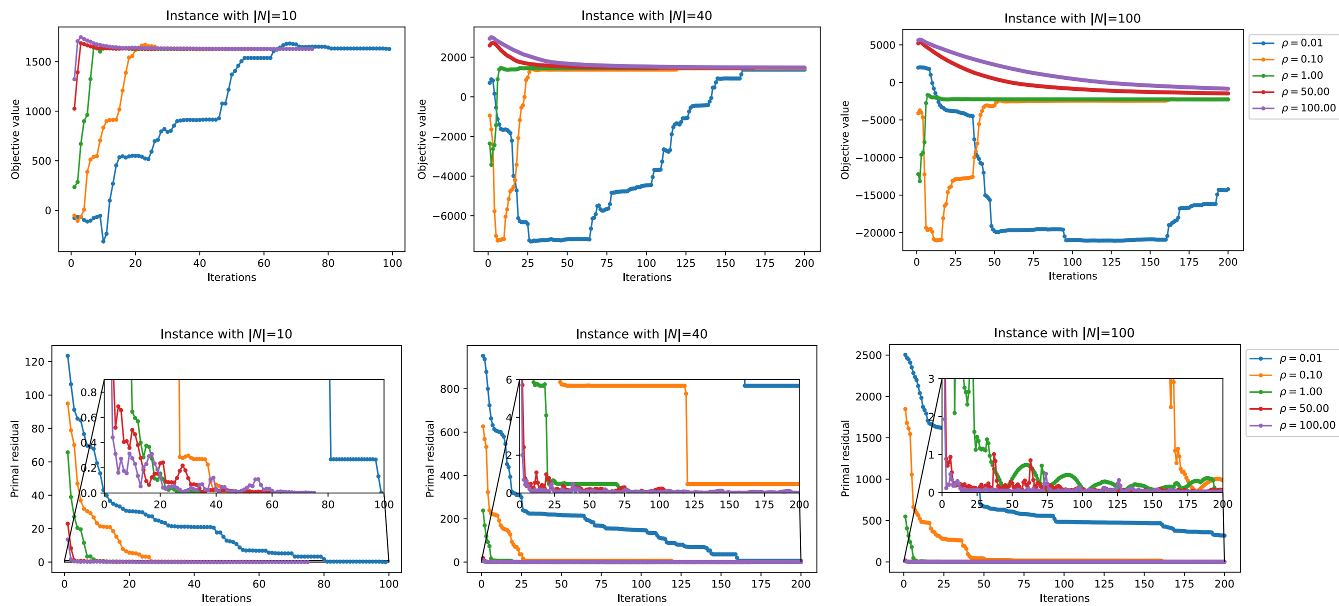


Fig. 6. Performance of ADMM for instances with different number of agents $|\mathcal{N}|$ and different values of ρ. For each instance, the evolution along the iterations of the objective value and the primal residual (with a zoom) for the different values of ρ are depicted.

that, the more agents the instance has, the more difficult is to verify (38). Therefore, it seems reasonable to set the value of ϵ^p bigger for instances with more number of agents.

Besides, it is worth mentioning that the theoretical results of the ADMM algorithm guarantee the convergence of the dual variables (21), which in this problem can be in interpreted as a consensus of the clearing prices between the agents. Therefore, it is interesting to also include as stopping criteria:

$$\left\| \lambda^{(k+1)} - \lambda^{(k)} \right\|_2 \leq \epsilon^d \tag{39}$$

to overcome the lack of convergence we observe for the instances with 80 and 100 agents.

Fig. 7 shows the evolution of the convergence of the dual variables for the instances with 80 and 100 agents (the behavior is analogous for the other instances). The case of $\rho = 1$ exhibits a really smooth behavior and it reaches the smallest value of the convergence of the dual variables.

Considering for the instances with 80 and 100 agents the alternative stopping criteria that the primal residual and the convergence of the dual variables reach values below $\epsilon^p = 0.1$ and $\epsilon^d = 10^{-3}$, respectively, we obtain the results of Table II (we only show the cases for which the algorithm has converged). As we can see, with this new stopping criteria, for the instance with 80 agents the algorithm converges for $\rho = 1$ in 89 iterations, and for the instance with 100 agents, it converges for $\rho = \frac{1}{\mathcal{N}} = 0.01$ and $\rho = 1$, in 179 and 45 iterations, respectively. Interestingly, for the instance with 100 agents the algorithm with $\rho = 1$ now stops just before the primal residual (see Figure 6(g)) starts to oscillate.

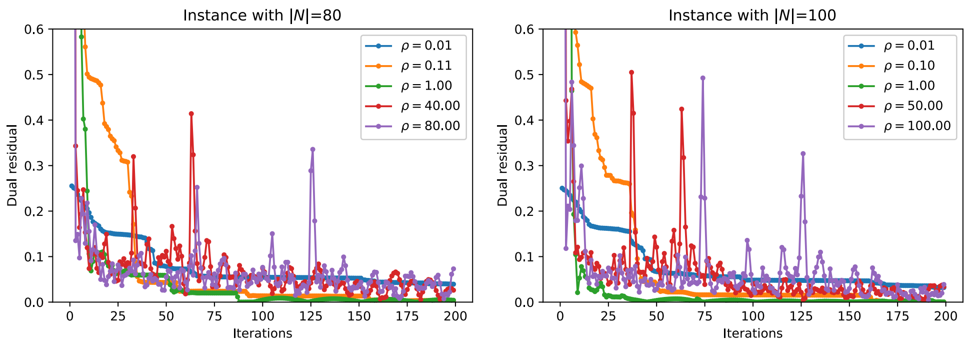
Taking into account the interpretation of both the primal residual, i.e., balance of the LEM, and the dual residual, i.e., consensus in the LEM prices, it would be perfectly feasible to set more relaxed values as stopping criteria in a real-life implementation, for example, $\epsilon^p = 1$ and $\epsilon^d = 0.1$. As we can see in Table III, with these relaxation of the stopping criteria, the algorithm converges really fast. Furthermore, the value of $\rho = 1$ continues to exhibit the best performance. Interestingly, despite of the relaxation of the stopping criteria, for $\rho = 1$ the algorithm reaches practically the same objective function as

TABLE II
OBJECTIVE VALUES, PRIMAL RESIDUALS, DUAL CONVERGENCE AND NUMBER OF ITERATIONS UNDER STOPPING CRITERIA $\epsilon^p = 0.1$ AND $\epsilon^d = 10^{-3}$

Instance ($\|\mathcal{N}\|$)	$\rho(\|\mathcal{N}\|)$	Objective Value	Primal	Dual	Iterations
80	1.00	3629.66	0.0053	0.0001	89
100	0.10	-2265.56	0.0910	0.0001	179
	1.00	-2242.36	0.0205	0.0010	45

TABLE III
OBJECTIVE VALUES, PRIMAL RESIDUALS, DUAL CONVERGENCE AND NUMBER OF ITERATIONS UNDER STOPPING CRITERIA $\epsilon^p = 1$ AND $\epsilon^d = 0.1$

Instance ($\|\mathcal{N}\|$)	$\rho(\|\mathcal{N}\|)$	Objective Value	Primal	Dual	Iterations
10	0.10	1627.69	0.2673	0.0177	81
	0.32	1627.68	0.2851	0.0957	27
	1.00	1627.85	0.5946	0.0645	11
	5.00	1633.73	0.0943	0.0911	15
	10.00	1646.50	0.2032	0.0532	14
20	0.05	2971.30	2.1337	0.0053	200
	0.22	2972.24	0.0065	0.0227	63
	1.00	2973.35	0.1557	0.0444	15
	10.00	3066.42	0.3877	0.0901	9
	20.00	3187.13	0.1557	0.0868	9
40	0.03	1432.91	5.6734	0.0035	200
	0.16	1444.14	0.4676	0.0207	120
	1.00	1451.67	0.4733	0.0166	21
	20.00	1971.32	0.3041	0.0836	15
	40.00	2601.25	0.1651	0.0903	11
80	0.01	2881.23	252.1029	0.0394	200
	0.11	3618.50	1.6777	0.0023	200
	1.00	3629.79	0.9309	0.0200	87
	40.00	9199.73	0.2210	0.0738	11
	80.00	10439.71	0.2279	0.0972	6
100	0.01	-3640.50	317.4238	0.0320	200
	0.10	-2266.22	0.7768	0.0011	167
	1.00	-2237.32	0.9687	0.0130	34
	50.00	4125.29	0.1969	0.0936	11
	100.00	4613.57	0.0414	0.0522	15



(a) Dual values convergence for instance with 80 agents.

(b) Dual values convergence for instance with 100 agents.

Fig. 7. Evolution of the convergence of the dual variables for instances with 80 and 100 agents. (a) Dual values convergence for instance with 80 agents. (b) Dual values convergence for instance with 100 agents.

before, so the final solution wouldn't get any worse despite terminating in fewer iterations.

Regarding the computational time of the algorithm, it is important to remember that in each iteration, the number of subproblems that need to be solved is equivalent to the number of agents in the community, where subproblems are similar to each other. Taking into account that they can be solved in parallel, the computational cost of the algorithm falls to the time needed to solve a subproblem. In our test, the average time required to solve a subproblem was about 0.35 seconds.

As a conclusion, this analysis shows that the penalty factor greatly influences the convergence properties of the proposed clearing algorithm. However, for the energy community analyzed in this work, a value of $\rho = 1$ shows a good performance in all the instances regarding convergence of both objective function, primal and dual residuals. Moreover, if the stopping criteria is relaxed to reasonable values considering a practical implementation of this framework, convergence properties, including number of iterations, reach very promising values.

As future research work, in view of the results, it would be interesting to define a stopping criteria depending on the number of agents. Furthermore, the definition of a dynamically chosen penalty factor could be helpful to speed up the convergence of the algorithm. The results suggest that it may be promising to start with big values of the penalty factor to quickly reach small values of the primal residual, and then decrease it to put more emphasis on the original objective function.

V. Conclusion

In this article, a community-based local market framework is proposed, from the clearing on a day-ahead basis to a final settlement accounting for actual energy exchanges, given the uncertainty in renewable generation. A case study of a residential neighborhood in Amsterdam, The Netherlands, is used as a real case for the testing of the developed framework. A decentralized market clearing process is introduced in order to minimize concerns regarding data privacy and communication burden, which shows good convergence and scalability properties for practical implementation in the analyzed case study. The RT problem aims at making operational decisions at an agent level, including storage operation, while taking into account the commitments acquired during the day-ahead clearing. To complete the market framework, a settlement process was added. This settlement aims at assigning the actual participation of each agent in the LEM. While some new regulation is needed to define the requirements for the CM, the proposed framework allows a seamless integration of a local electricity market into the current power system. The adoption of such a LEM framework would benefit the members of the community as shown in the case study, and would provide a price signal for them to manage and make decisions concerning their own assets. A further analysis of the properties of the proposed market mechanism to set prices and final assignments, consideration of network-related losses, and definition of dynamic stopping criteria for the ADMM algorithm are among author's priorities for further research.

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