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Local Energy Markets: Paving the Path Towards Fully Transactive Energy Systems

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***Abstract*—Triggered by the increased fluctuations of renewable energy sources, the European Commission stated the need for integrated short-term energy markets (e.g., intraday), and recognized the facilitating role that local energy communities could play. In particular, microgrids and energy communities are expected to play a crucial part in guaranteeing the balance between generation and consumption on a local level. Local energy markets empower small players and provide a stepping stone towards fully transactive energy systems. In this paper we evaluate such a fully integrated transactive system by (1) modelling the energy resource management problem of a microgrid under uncertainty considering flexible loads and market participation (solved via two-stage stochastic programming), (2) modelling a wholesale market and a local market, and (3) coupling these elements into an integrated transactive energy simulation. Results under a realistic case study (varying prices and competitiveness of local markets) show the effectiveness of the transactive system resulting in a reduction of up to 75% of the expected costs when local markets and flexibility are considered. This illustrates how local markets can facilitate the trade of energy, thereby increasing the tolerable penetration of renewable resources and facilitating the energy transition.**

***Index Terms*—Demand response, local electricity markets, microgrids, transactive energy, smart grids, stochastic optimization.**

NOTATION

Indices:

e	energy storage systems (ESSs)
i	distributed generation (DG) units
l, m, s, t, v	loads, markets, scenarios, periods, electric vehicles (EVs)

Sets and subsets:

Ω_{DG}, Ω_{load}	set of DG units/loads
Ω^{d}_{DG},Ω^{nd}_{DG}	subset of dispatchable/non-dispatchable DG units
Ω^{curt}_{load},Ω^{inte}_{load}	subset of curtailable/interruptible loads
Ω^{shift}_{load}	subset of shiftable loads

Parameters:

C_{DG}	generation cost of DG unit (m.u./kWh)
C_{ESS-},C_{EV-}	discharging cost of ESS/EV (m.u./kWh)
C_{curt},C_{inte},C_{shift}	load curtailment/interruption/shift cost (m.u./kWh)
C_{imb}	grid imbalance cost (m.u./kWh)
MP	electricity market price (m.u./kWh)
N_e, N_i, N_l	number of ESS/DG/loads
N_m, N_s, N_v	number of markets/scenarios/EVs
$P_{curt_{max}}$	maximum load reduction of Ω^{curt}_{load} (kW)
$P_{DG_{max/min}}$	maximum/minimum power of dispatchable DGs (kW)
$P_{DG_{nd}}$	forecast power of non-dispatchable DGs (kW)
$P_{ESS/EV^{+}_{max}}$	maximum charge rate of ESSs/EV (kW)
$P_{ESS/EV^{-}_{max}}$	maximum discharge rate of ESSs/EV (kW)
$P_{ESS_{max/min}}$	maximum/minimum energy capacity of ESSs (kWh)
$P_{EV_{max/min}}$	maximum/minimum energy capacity of EVs (kWh)
$P_{EV_{trip}}$	forecasted energy demand for EVs' trip (kWh)
P_{load}	forecasted active power of loads (kW)
$P_{offer_{max/min}}$	maximum/minimum energy offer in markets (kW)
P_{shift}	forecasted power of Ω^{shift}_{load} in T_{shift} (kW)
$P_{shift_{max}}$	maximum load shifted of Ω^{shift}_{load} in T_{shift} (kW)
T	number of periods
T_{shift}	shift interval of Ω^{shift}_{load}
T^{start}_{shift} /T^{end}_{shift}	earliest/latest possible period for load shift of Ω^{shift}_{load}
$\eta_{EV^{+}/EV^{-}}$	charging/discharging efficiency of EVs
$\pi(s)$	probability of scenario s

Variables:

E_{total}	total day-ahead solution cost (m.u.)
MT	total day-ahead market transactions (m.u.)
OC	total day-ahead operation cost (m.u.)
p_{DG}	active power generation of DGs (kW)
$p_{ESS^{+}}$/$p_{ESS^{-}}$	active power charge/discharge of ESSs(kW)
p_{ESS}	energy stored in ESSs (kWh)
$p_{EV^{+}}$/$p_{EV^{-}}$	active power charge/discharge of EVs (kW)
p_{EV}	energy stored in EVs (kWh)
p_{inte}	active power interruption of Ω^{inte}_{load} (kW)
p_{curt}	active power reduction of Ω^{curt}_{load} (kW)
p_{shift}	shift active power of Ω^{shift}_{load} in T_{shift} (kW)
$p_{shift^{-}}$/$p_{shift^{+}}$	reduced/increased power of Ω^{shift}_{load} in T_{shift} (kW)
p_{sell} / p_{buy}	power sell/buy offer (bid) to the market (kW)
$p_{imb^{+}}$/$p_{imb^{-}}$	exceeded/non-supplied power of DGs units (kW)

Binaries:

x_{DG}	state of DG units
$x_{ESS^{-}/EV^{-}}$	discharging state of ESSs/EVs
$x_{ESS^{+}/EV^{+}}$	charging state of ESSs/EVs
x_{inte}	state of interruptible load
x_{sell}/x_{buy}	sell/buy offer to a market

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I. INTRODUCTION

THE energy transition foresees an increased adoption of fluctuating renewable generation, which needs to be matched by increased demand-side flexibility and storage. Current European electricity systems employ exchanges for large-scale ancillary service providers and the participation in wholesale (WS) markets is only possible for small generators when associated to energy aggregators or brokers [1].

One solution for the high penetration of distributed generation (DG) is to expand the distribution grid, however, the costs could be prohibitive [2]. Another solution is to handle technical constraints with active control to manage local resources, storage systems and demand response (DR) programs [3], however, this may raise privacy concerns [4].

In this context, moving towards a transactive energy (TE) system, defined by the GridWise Architecture Council as "*a set of economic and control mechanisms that allow the dynamic balance of supply and demand across the entire electrical infrastructure using value as a key operational parameter*" [5], seems to be a promising step to fulfil the needs of the current situation. A TE framework envisages that mid- to small-sized generation and consumption can automatically negotiate their actions with each other using effective energy resource management (ERM) systems and electronic market algorithms allowing a dynamic balance of supply and demand. Despite the efforts made so far, fully TE systems at the distribution and retail market level are largely missing mainly due to the complex scenario that such systems pose [6], [7]. In such conditions, local energy communities have been recognized by the European Commission (EC) as a potential way to perform energy management. Local energy communities have been successfully deployed in several countries [8], [9] with diverse characteristics (e.g., population size, location, type of renewable used). This variability gives raise to different needs and therefore an opportunity to trade and energy surplus. Moreover, the EC has stated the need for an adaptation of market and grid operation rules to the more flexible nature of the market [8]. In fact, this leads to the ultimate need for a more dynamic marketplace that goes from the intraday timescale towards the intrahourly scale. This flexibilization is necessary in order to cope with the large variation of renewable generation at near real-time, while still allowing the involved players to establish some commitments in advance (e.g., day-ahead or some hours-ahead in a smart grid perspective).

Therefore, the European Commission has declared that integrated short-term local markets (LMs), as we discuss in this paper, are still missing [8]. A LM is a platform on which individual consumers and prosumers trade energy supporting regional scopes such as a neighbourhood environment [10]. Advantages of LMs include that (1) more self-generated electricity can be consumed locally, which alleviates transport losses [11] and reduces the risk of backfeeding at MV/LV transformers; (2) the local economy is strengthened, which provides new opportunities for local industry and regional business, and (3) they support the development of the smart grid [12]. While system components have been addressed in related work (Sect. II), our work integrates local optimization with both local and global exchange.

This paper presents an integrated simulation environment of energy communities including the market clearing process for WS and LMs with traditional energy resource optimization approaches, in order to analyse the impact of TE management and LMs in power systems. We contribute to the state of the art in the following ways:

- Adopting an integrated model for simulation which enables assessing the impact of LMs in a TE environment. The proposed framework, besides providing a new model for LMs, allows evaluating the effects of a large number of participants (MGs[1]) in the electricity market as well as to refine business models on a system and small player level.
- To achieve this objective, a two-stage stochastic programming model is implemented to solve the day-ahead energy resource management (ERM) problem under uncertainty taking into account MG context, flexibility and market transaction either to buy or sell energy.
- Considering the expected needs, the WS and LMs are executed, bringing together different aggregators as well as small players that desire to participate in market negotiations directly.
- Finally, we contribute with an evaluation of this paradigm through simulation, with comparison to baseline DR allocations inspired by current markets.

In this paper, we hypothesize that players receive a competitive advantage when being able to exchange energy with their peers (i.e., LMs), outperforming two alternative scenarios: without market access (current situation in many countries), and when it is possible to only trade in the WS market directly or through a market broker.

II. Related work

Electricity markets are undergoing changes to adapt to the high penetration of renewable resources; since consumers are becoming prosumers, traditional passive and static supply contracts become insufficient, as they cannot adequately capture the fluctuating value of energy and flexibility. Two-sided markets have been adopted in electric power systems to provide more dynamic and efficient allocations, e.g., local energy markets were introduced as a way to cope with fluctuating renewable energy sources [13]. Recently, LMs were identified as promising to reduce costs, effectively managing DR and supporting the development of the smart grid [12], yet lacking quantitative support. Our work complements this line of work by providing a numerical comparison of how LMs can reduce costs under different scenarios.

Recent works have proposed new market solutions to cope with DR, for example, by proposing an extension of the WS market with a real-time market that will offer transmission system operators additional balancing resources [14]. In contrast, our work integrates local optimization with bidding options in both local and WS markets. Another related proposal are day-ahead micro-markets, whose objective is to organize local resources using market-based rules to participate in aggregated form in the day-ahead WS market [15]. They assume a micro-market operator whose aim is to maximize the profits of the MG, similar to the ERM in our WS market model. However, in contrast we add a new LM as a subsequent phase that happens after the WS market is cleared.

Few works have tackled the problem of modelling the bidding process for small participants. For example, Odegaard et al. [16] proposed a model for an aggregator that can sell and buy electricity on behalf of a group of prosumers in a

[1] In this paper, a microgrid (MG) refers to a distribution system with loads and DG, that can be operated in a controlled and coordinated way. The MG considered in our case study represents an energy community connected to the rest of the grid and controlled by an aggregator [8], [9].

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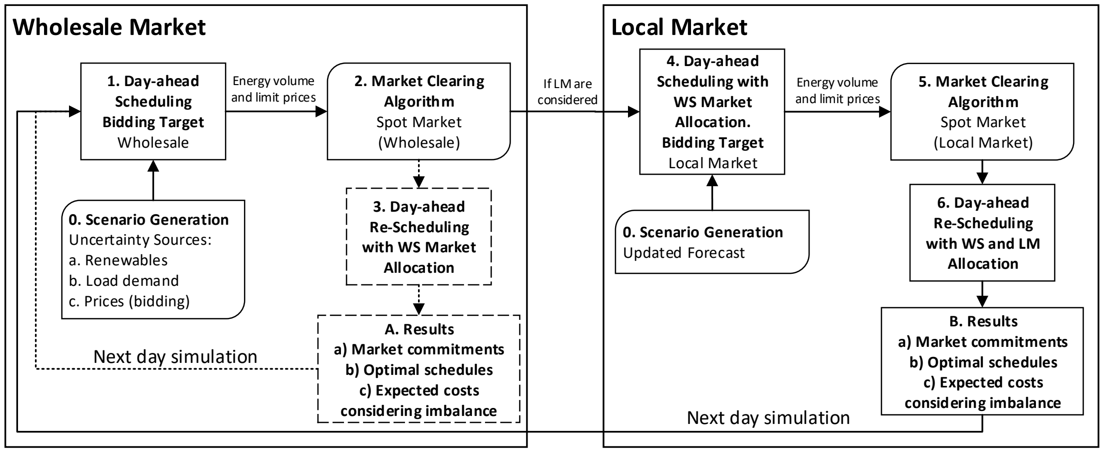

Fig. 1. The proposed methodology starts with an initialisation step (0) that generates the scenario, followed by six steps where the MG solves the ERM scheduling and can trade in two different markets, first a WS market after which there is an updated forecast, a new scheduling is performed and now the MG can trade in a LM. At the end of the simulation, we assume that there is an imbalance market that accounts for any deviation.

WS market. In contrast, we present an integrated modelling of the bidding process and market modelling for both local and WS markets.

Simulation environments for power systems and energy markets [1] have provided valuable insights without the burden of risking existing infrastructure, however, current tools lack the capacity to accurately model both the ERM problem and the market simulation. Here, we show numerical results of a simulation that integrates the ERM considering market bids (in local and WS markets) and comparing different scenarios highlighting the benefits (i.e., reducing costs) of LMs. Next, we describe the integrated framework that considers LM.

III. Integrated transactive energy system

This section presents the main contribution of this work and is divided into three main subsections introducing the methodology, mathematical model and markets.

A. Methodology

The proposed framework comprises the following sequence of steps, as depicted in Fig. 1. Our experiments will compare three different cases: no market access (step 1), only WS market access (steps 1-3), and WS and LMs (steps 1-6).

0) Each scenario has uncertainty from three main sources: generators, loads and markets (see Section III-B1).
1) The first step is to solve the ERM day-ahead scheduling by using two-stage stochastic programming including bidding options for a WS market, if available.
2) The day-ahead WS market takes place and provides a response to every participant (i.e., if the bids/asks were accepted or not). Since this is a WS market, we assume the trading volume to be greater than in the LM.
3) Based on the market clearing, a re-scheduling is computed. WS market forecasts are updated to reflect information arriving as time moves closer to the delivery interval. If the LM is not available, the simulation terminates by computing the residual imbalance costs.
4) If the LM is available, the next step computes a second ERM including bidding options in the LM, exploiting the updated forecast and thus aiding short-term balancing.
5) The LM is cleared assuming that only local MGs can trade.
6) A final re-scheduling is performed having as a result the expected costs considering imbalance penalties.

B. Scheduling and Bidding Optimization under Uncertainty

The uncertainty modelling and the mathematical formulation of ERM problem are described below.

1) Uncertainty representation: In this paper, to overcome the lack of historical data to build accurate case-studies, we assume that a correct set of scenarios that simulate real-world behaviour can be generated considering forecast and associated errors based on previous experiences. The uncertainty comes from different sources such as: i) renewable generators, ii) load profiles, and iii) market prices.

We apply the technique for scenario generation (and scenario reduction) used in [17]. In a first step, a large number of scenarios is generated by Monte Carlo Simulation (MCS). The MCS uses the probability distribution function of the forecasted errors (which can be obtained from historical data) to create a number of scenarios according to $X^s(t) = x^{forecast}(t) + x^{error,s}(t)$, where $x^{error,s}$ is a zero-mean noise with standard deviation σ. To simplify, all forecast errors for the uncertain inputs are represented by a normal distribution function. A high accuracy is obtained by using a large set of scenarios. However, this increase in accuracy comes with a computational cost associated with the increase in the number of variables considered, and therefore, including all scenarios may turn the model into a large-scale optimization problem [17].

To handle the computational burden and still obtain accurate results, a standard scenario reduction technique that excludes scenarios with low probabilities and combines those that are close to each other in terms of statistical metrics is applied (for a complete description see [17]). In this way, the size of the problem is reduced without losing the main statistical characteristics of the initial dataset.

2) Two-stage stochastic model: The first-stage decisions are the WS and LM offers as well as the dispatchable generation schedules. The second-stage decisions are the ESS/EV charging and discharging decisions and DR requests. The later decisions can be done close to real-time in next day but first-stage decisions need to be addressed day-ahead due to market closing times. The objective function minimizes the expected day-ahead operation costs over a scheduling horizon T (i.e., the next 24 hrs) [17]:

$$\text{Minimize} \quad E_{total} = OC + MT \tag{1}$$

where OC represents the costs associated with the management of the resources:

$$OC = \sum_{t=1}^{T} \sum_{i\in\Omega_{DG}^{d}} p_{DG(i,t)} \cdot C_{DG(i,t)} + \sum_{s=1}^{N_s}\sum_{t=1}^{T} \left(\begin{array}{l} \sum_{i\in\Omega_{DG}^{nd}} p_{DG(i,t,s)} \cdot C_{DG(i,t)} + \\ \sum_{e=1}^{N_e} p_{ESS^-(e,t,s)} \cdot C_{ESS^-(e,t)} + \\ \sum_{v=1}^{N_v} p_{EV^-(v,t,s)} \cdot C_{EV^-(v,t)} + \\ \sum_{l\in\Omega_{load}^{curt}} p_{curt(l,t,s)} \cdot C_{curt(l,t)} + \\ \sum_{l\in\Omega_{load}^{inte}} p_{inte(l,t,s)} \cdot C_{inte(l,t)} + \\ \sum_{l\in\Omega_{load}^{shift}} p_{shift^-(l,t,s)} \cdot C_{shift(l,t)} + \\ \sum_{l=1}^{N_l} p_{imb^-(l,t,s)} \cdot C_{imb^-(l,t)} + \\ \sum_{i=1}^{N_i} p_{imb^+(i,t,s)} \cdot C_{imb^+(i,t)} \end{array} \right) \cdot \pi(s) \tag{2}$$

while MT is the term that describes the expected market transactions in any given number of markets:

$$MT = \sum_{s=1}^{N_s}\sum_{t=1}^{T} \left(\sum_{m=1}^{N_m} \left(p_{buy(m,t)} - p_{sell(m,t)}\right) \cdot MP_{(m,t,s)} \right) \cdot \pi(s). \tag{3}$$

The objective function is subject to the following constraints:

a) Energy balance constraint: states that the amount of generated energy should be equal to the amount of consumed energy at every instant t. This constraint also includes the expected energy that may be bought/sold in the markets:

$$\begin{array}{l} \sum_{i\in\Omega_{DG}^{d}} p_{DG(i,t)} + \sum_{i\in\Omega_{DG}^{nd}} p_{DG(i,t,s)} + \\ \sum_{v=1}^{N_v} (p_{EV^-(v,t,s)} - p_{EV^+(v,t,s)}) + \\ \sum_{e=1}^{N_e} (p_{ESS^-(e,t,s)} - p_{ESS^+(e,t,s)}) + \\ \sum_{l=1}^{N_l} (p_{curt(l,t,s)} + p_{inte(l,t,s)} + p_{shift^-(l,t,s)}) - \\ \sum_{l=1}^{N_l} (p_{load(l,t,s)} + p_{shift^+(l,t,s)}) + \sum_{m=1}^{N_m} (p_{buy(m,t)} - p_{sell(m,t)}) + \\ \sum_{i\in\Omega_{DG}^{nd}} p_{imb^+(i,t,s)} - \sum_{l=1}^{N_l} p_{imb^-(l,t,s)} = 0 \quad \forall t, \forall s. \end{array} \tag{4}$$

Notice that p_{imb^+}/p_{imb^-} represent the imbalance energy that occurs when generation is higher than demand or vice versa. By putting a high cost to this imbalance energy, we force the model to avoid this condition as much as possible.

b) DG units constraints: Maximum and minimum power limits can be formulated as:

$$\begin{array}{l} p_{DG(i,t)} \leq x_{DG(i,t)} \cdot P_{DG_{max}(i,t)}, \\ p_{DG(i,t)} \geq x_{DG(i,t)} \cdot P_{DG_{min}(i,t)} \quad \forall t, \forall i \in \Omega_{DG}^{d} \end{array} \tag{5}$$

where x_{DG} are binary variables representing the status of dispatchable DG units (i.e., connected/disconnected status). On the other hand, non-dispatchable DGs are modelled according to the generated scenarios:

$$p_{DG(i,t,s)} = P_{DG_{nd}(i,t,s)} \quad \forall t, \forall i \in \Omega_{DG}^{nd}, \forall s. \tag{6}$$

c) Energy storage systems constraints: Constraints on two binary variables per ESS ensure that charging and discharging do not occur simultaneously:

$$x_{ESS^+(e,t,s)} + x_{ESS^-(e,t,s)} \leq 1 \quad \forall t, \forall e, \forall s. \tag{7}$$

The maximum discharge limit for each ESS is given by:

$$p_{ESS^-(e,t,s)} \leq P_{ESS^-_{max}(e,t)} \cdot x_{ESS^-(e,t,s)} \quad \forall t, \forall e, \forall s. \tag{8}$$

The maximum charge limit for each ESS is given by:

$$p_{ESS^+(e,t,s)} \leq P_{ESS^+_{max}(e,t)} \cdot x_{ESS^+(e,t,s)} \quad \forall t, \forall e, \forall s. \tag{9}$$

The maximum ESS capacity limit is given by:

$$p_{ESS(e,t,s)} \leq P_{ESS_{max}(e,t)} \quad \forall t, \forall e, \forall s. \tag{10}$$

The minimum ESS stored energy to be guaranteed at the end of each period can be represented such as:

$$p_{ESS(e,t,s)} \geq P_{ESS_{min}(e,t)} \quad \forall t, \forall e, \forall s. \tag{11}$$

The ESS balance can be formulated as:

$$\begin{array}{l} p_{ESS(e,t,s)} = p_{ESS(e,t-1,s)} + \eta_{ESS^+(e)} \cdot p_{ESS^+(e,t,s)} \\ -\frac{1}{\eta_{ESS^-(e)}} \cdot p_{ESS^-(e,t,s)} \quad \forall t, \forall e, \forall s. \end{array} \tag{12}$$

d) EVs constraints: Two binary variables are used to guarantee that EVs do not charge and discharge simultaneously:

$$x_{EV^+(v,t,s)} + x_{EV^-(v,t,s)} \leq 1 \quad \forall t, \forall v, \forall s. \tag{13}$$

The maximum discharge limit for each EV is given by:

$$p_{EV^-(v,t,s)} \leq P_{EV^-_{max}(v,t)} \cdot x_{EV^-(v,t,s)} \quad \forall t, \forall v, \forall s. \tag{14}$$

The maximum charge limit for each EV is given by:

$$p_{EV^+(v,t,s)} \leq P_{EV^+_{max}(v,t)} \cdot x_{EV^+(v,t,s)} \quad \forall t, \forall v, \forall s. \tag{15}$$

The maximum EV capacity limit is given by:

$$p_{EV(v,t,s)} \leq P_{EV_{max}(v,t)} \quad \forall t, \forall v, \forall s. \tag{16}$$

The minimum EV stored energy to be guaranteed at the end of each period can be represented such as:

$$p_{EV(v,t,s)} \geq P_{EV_{min}(v,t)} \quad \forall t, \forall v, \forall s. \tag{17}$$

The EV balance can be formulated as:

$$\begin{array}{l} p_{EV(v,t,s)} = p_{EV(v,t-1,s)} - P_{EV_{trip}(v,t)} + \\ \eta_{EV^+(v)} \cdot p_{EV^+(v,t,s)} - \frac{1}{\eta_{EV^-(v)}} \cdot p_{EV^-(v,t,s)} \\ \forall t, \forall v, \forall s. \end{array} \tag{18}$$

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e) Demand response: Flexibility in the loads is modelled by direct load control programs in which consumers voluntarily participate and receive a monetary compensation if their loads are reduced, disconnected or shifted [18]. The types of flexible loads used in this model are described below:

- Curtailable loads.
  The maximum active power that each load can be reduced is formulated as:

$$0 \leq p_{curt(l,t,s)} \leq P_{curt_{max}(l,t,s)} \quad \forall t, \forall l \in \Omega_{load}^{curt}, \forall s. \tag{19}$$

- Interruptible loads.
  Interruptible loads can be disconnected at any given time for a compensation cost. A binary variable is used to control the on/off status of the considered loads:

$$p_{inte(l,t,s)} = P_{load(l,t,s)} \cdot x_{inte(l,t,s)} \quad \forall t, \forall l \in \Omega_{load}^{inte}, \forall s. \tag{20}$$

- Shiftable volume loads.
  Shiftable loads allow a shift or modification in their profiles as long as the total volume over such shift period is respected. Eq. (21) is used to accomplish that condition:

$$T_{shift}^{start}; T_{shift}^{end} \in T_{shift}(l) \quad \forall l \in \Omega_{load}^{shift}$$

$$\begin{gathered}\sum_{T_{shift}^{start}}^{T_{shift}^{end}} p_{shift(l,t,s)} = \sum_{T_{shift}^{start}}^{T_{shift}^{end}} P_{shift(l,t,s)} \\ \forall t \in T_{shift}, \forall l \in \Omega_{load}^{shift}, \forall s.\end{gathered} \tag{21}$$

Moreover, the maximum quantity of shiftable load is giving by the follow set of equations:

$$\begin{aligned}&p_{shift(l,t,s)} \leq P_{shift(l,t,s)} + P_{shift_{max}(l,t,s)}, \\ &p_{shift(l,t,s)} \geq P_{shift(l,t,s)} - P_{shift_{max}(l,t,s)}, \\ &\forall t, \forall l \in \Omega_{load}^{shift}.\end{aligned} \tag{22}$$

The negative (i.e., the reduction of load) or positive shift (i.e., the increase in load) for each period is captured using the next set of equations:

$$p_{shift^{+}(l,t,s)} \geq 0 \quad \forall t, \forall l \in \Omega_{load}^{shift}, \forall s, \tag{23}$$

$$p_{shift^{-}(l,t,s)} \geq 0 \quad \forall t, \forall l \in \Omega_{load}^{shift}, \forall s, \tag{24}$$

$$\begin{aligned}&P_{shift(l,t,s)} + p_{shift^{+}(l,t,s)} = p_{shift(l,t,s)} + p_{shift^{-}(l,t,s)} \\ &\forall t, \forall l \in \Omega_{load}^{shift}, \forall s.\end{aligned} \tag{25}$$

f) Market/bidding constraints: Market rules due to minimum required amount to access or strategical planning.

$$\begin{aligned}p_{buy}(m,t) &\leq P_{offer_{max}}(m,t) \cdot x_{buy(m,t)} && \forall t, \forall m, \\ p_{buy}(m,t) &\geq P_{offer_{min}}(m,t) \cdot x_{buy(m,t)} && \forall t, \forall m, \\ p_{sell}(m,t) &\leq P_{offer_{max}}(m,t) \cdot x_{sell(m,t)} && \forall t, \forall m, \\ p_{sell}(m,t) &\geq P_{offer_{min}}(m,t) \cdot x_{sell(m,t)} && \forall t, \forall m.\end{aligned} \tag{26}$$

where $x_{sell(m,t)} + x_{buy(m,t)} \leq 1 \quad \forall t$ are binary variables used to guarantee that the market transactions in each period are unique. Each MG optimizes its resources and if necessary makes bids in the WS and LMs which we described in the next section.

C. Markets

In our experiments, simultaneous auctions are held for each power delivery interval corresponding to hours of the day. Each bid/ask is a tuple $< t, q, p >$ where a participant (i.e., MG) bids for q energy units at a maximum price p for timeslot t. We model markets as a *clearing house* [19], i.e., clearing happen at a fixed time once at the end of the trading period. Traders submit bids and asks until the end of the trading period and these are used to determine the supply and demand curves for energy. The price at which supply equals demand is known as the *equilibrium price*. Models on how traders decide on what offers to make are known as *price formation* models [19]. *Zero intelligence* (ZI) agents [20] are a well-known trading approach, in particular ZI-U (unconstrained) agents pick a bid or ask from anywhere within a given price range and ZI-C (constrained) agents[2] pick offers constrained to be profitable if accepted; they are not allowed trade with directly negative results, that is, to sell below cost or buy above value.

In our experiments, we simulate ZI-C agents that make bids and asks, this is, their offers are constrained in a range (p_{min}, p_{max}). There are two main differences between the considered markets: 1) the information available before the market clearing, i.e., the LM always happens after the WS market was cleared; 2) the volume and liquidity of energy traded in each market, i.e., LMs presents smaller amounts of energy traded, as well as liquidity than the WS market.

LMs are inherently diverse, and the smaller scale gives rise to large diversity in the possible composition of the participants, which contrasts national markets in which local fluctuations average out. In order to capture the LM characteristics that are most relevant for the local optimisation, we evaluate different *success rates* while controlling for *expected market price*. The success rate represents the probability of the market to accept the bid, as a fundamental and abstract model subsuming market liquidity and price competition. By varying success rate, we get insights under different situational competitiveness, independent of whether it is caused by a lack of competition, an abundance of complementary market participants, or other factors. We induce the desired success rate in experiments by varying the competing offer distribution in the market.

IV. Case Study

Our proposed methodology is tested using a case study[3] based on a 25-bus MG that represents a residential energy community with 22 DGs (5 dispatchable units and 17 PV generators), 2 ESSs, 34 EVs, and 90 households with loads of different classes including inflexible, curtailable, shiftable and interruptible loads. Table I outlines the resources available in the MG.

With these available devices, we generate the required data for one week of simulation based on a real forecast of energy generation and load consumption. To summarize, prices of

[2] Gode and Sunder [20] showed that a market consisting of ZI-C agents produced results similar to the allocative efficiency of a market with human traders.

[3] Published in: http://www.gecad.isep.ipp.pt/ies/public-data/ites

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DG/loads and household consumption patterns used in the paper are available online[3]. The solar radiation forecast was based on the profiles from a regular week.[4] The selected week includes four regular days (i.e., following a typical solar radiation pattern), and three atypical profiles (corresponding to cloudy days). Regarding the load, one typical pattern was used to generate the forecast of consumption of week days, while a different pattern was used for weekend days. EV schedules were created using the tool presented in [21]. WS market prices correspond to real data taken from the EPEX Spot market in the week of August 7-13, 2017.[5] LMs were simulated assuming 99 other MGs with similar characteristics (capacity, forecasts) to the one described above, this is, a LM is composed of 100 participants (MGs) and each MG is composed of different loads, generators and ESS.

The uncertainty was incorporated in a first step by creating 5000 scenarios for PV generation, load consumption and market price variations. For the PV uncertainty generation, an error of 15% was used for regular days, while an error of 20-25% was used for the cloudy days (to add more uncertainty). For the load and market prices, errors of 10% and 20% were used respectively. The errors follow a normal distribution according to Sect. III-B1. In a second step, the number of scenarios was reduced to 100 scenarios with the method from [17].

The research work was developed using a computer with an Intel Xeon W3565 processor and 6 GB of RAM running Windows 10. MATLAB 2014b and TOMLAB 8.1 64 bits with CPLEX solver (version 12.5) were used to solve the two-stage stochastic model, whereas JAVA JDK1.7 was used to simulate market clearing algorithms.

TABLE I
AVAILABLE ENERGY RESOURCES: CAPACITY OF THE ENERGY RESOURCES, FORECAST RANGE OF VARIABLE INPUTS AND LIMITS CONSIDERED IN THE WS AND LM

Energy Resources		Prices (m.u./kWh)	Capacity (kW)	Units
DGs		0.07-0.11	10-100	5
External Supplier		0.074-0.16	0-150	1
ESS	Charge	-	0-16.6	2
	Discharge	0.03	0-16.6	
EV	Charge	-	0-111	34
	Discharge	0.06	0-111	
Loads	Inflex	-	6.47-21.9	15
DR	Curtailable	0.0375	4.06-8.95	30
	Interruptible	0.085	6.26-14.03	20
	Shiftable	0.01	3.51-8.80	25
			Forecast (kW)	
Photovoltaic		-	0-106.81	1 (17agg.)
Load		-	35.82-83.39	90
			Limits (kW)	
WS Market		0.021-0.039	10-85	1
Local Market		-	2-40	1

V. EXPERIMENTS AND RESULTS

We applied our methodology to the case study presented in Section IV. First, we present results on a base case without market access and later we evaluate the impact of adding WS and LMs. In each case we consider two distinct flexibility cases, without flexibility (i.e., all the loads are inflexible) and with flexibility (as described in Table I). Our experimental design is intended to show that improvements persist under different conditions (e.g., variations in prices due to market arbitrage, lower liquidity and shorter time to delivery), and that they are not simply due to, e.g. prices being equal.

A. Scenario: base case (no market access)

The base case assumes that the MG has no access to any market, rather relies on an external supplier.[6] The stochastic scheduling model is applied to optimize the resources and minimize the costs over the 7 days of simulation. Table II presents the total cost by using only WS market, and both WS and LM (WS+LM with 75% success rate and equal prices for both markets) while contrasting availability and unavailability of flexible loads. Improvements are calculated w.r.t. no-flexibility and no-market-access (leftmost column). It can be seen an improvement in all cases when the MG has access to the LMs, i.e., highlighting the advantages provided by local transactions. Also, it is worth noting that the incremental improvement considering WS+LM is smaller when flexibility loads are available. This can be explained by the fact that flexible loads significantly contribute to decrease operational costs, thus mitigating the improvements provided by the LMs. On the other hand, when flexible loads are not available, LMs are fully exploited intensifying the gains provided by the access to them.

B. Scenario: access to WS and LM

To evaluate the impact of both markets on a MG, we analyse different cases varying (1) the success rate, with values of {25%, 50%, 75%, 95%}, for bids/asks to be accepted in the LM, (2) a price difference between the WS and the LM with values $\{\pm 75\%, \pm 50\%, \pm 25\%, equal\}$, for example, $+75\%$ means that the LM is 75% more expensive than the WS, and (3) the two distinct flexibility cases.

Fig. 2(a) clearly shows that the percentage of improvement with LMs is tightly related with the success of an offer to be accepted in the LM. The success rate can be learned by the trader, which future work may take into consideration in the optimisation. Regarding the price variation between WS and LM, Fig. 2(b) shows that the MG can take advantage of this situation achieving a higher profit when the price difference is large. This behaviour is explained by the optimization model which foresees whether the price is better for a sell offer (i.e., when the price is higher) or a buy offer (i.e., when the price is lower).

[4]Taken from http://meteo.isep.ipp.pt
[5]Available online in https://www.epexspot.com/

[6]We established a variable tariff for the external supplier based on real tariffs for the year 2016 provided by the Energy Services Regulatory Authority (ERSE) in Portugal: http://www.erse.pt→electricity→tariff and prices→Tarifas de anos anteriores→Tarifas Reguladas em 2016.

TABLE II
COSTS USING ONLY WS MARKET, OR BOTH WS AND LM (WS+LM) WITH 75% SUCCESS RATE AND EQUAL PRICES FOR BOTH MARKETS. IMPROVEMENTS ARE CALCULATED W.R.T. NO-FLEXIBILITY NO-MARKET-ACCESS (NO MA) REFERENCE.

	No Flexibility					Using flexibility					
	No MA	WS	Imp (%)	WS+LM	Imp (%)	No MA	Imp (%)	WS	Imp (%)	WS+LM	Imp (%)
day 1	72.68	41.84	42.43	31.37	56.83	60.41	16.87	32.90	54.73	27.19	62.58
day 2	48.28	34.06	29.46	26.08	45.99	42.35	12.28	24.11	50.07	23.85	50.59
day 3	47.88	25.48	46.79	19.49	59.28	41.46	13.41	24.19	49.47	24.15	49.56
day 4	87.05	57.48	33.96	44.31	49.09	79.69	8.44	45.31	47.95	42.93	50.67
day 5	61.43	30.15	50.91	28.33	53.88	54.45	11.34	28.24	54.02	27.27	55.61
day 6	56.64	25.15	55.59	23.17	59.09	49.81	12.07	29.38	48.13	22.67	59.98
day 7	44.49	21.12	52.53	16.38	63.18	38.37	13.74	15.63	64.86	17.08	61.61
	418.45	**235.28**	**43.77**	**189.13**	**54.80**	**366.55**	**12.43**	**199.76**	**52.26**	**185.14**	**55.75**

Fig. 2(c) shows the total energy traded after the seven days of simulation in the WS and LM considering price variations in the LM. The results show that the MG mainly uses the WS market to buy energy needed to supply its demand. On the contrary, the MG uses the LM to buy or sell, depending on the price. This also confirms the behaviour show in Fig. 2(b). For instance, the MG mainly uses the LM to sell energy when the price is high (increasing incomes) and to buy energy when the price is low (reducing operational cost).

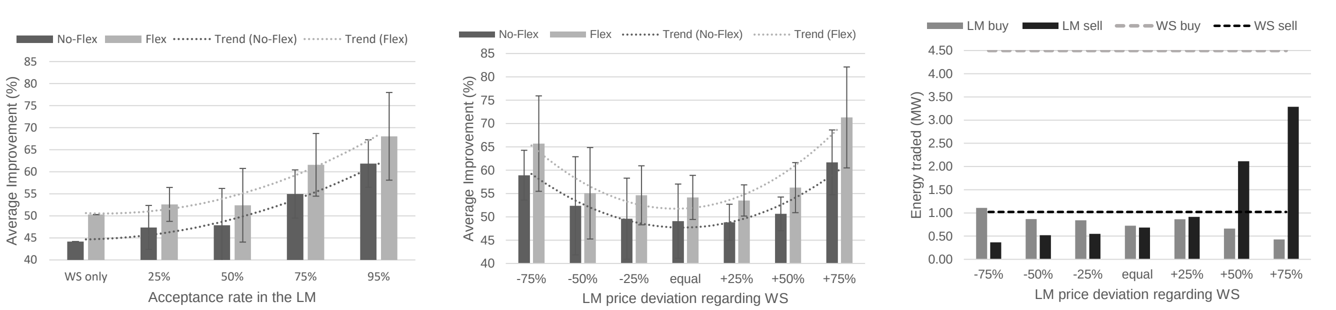
Regarding the behavior of LMs, Figs. 3(a) and 3(b) depict the equilibria distribution of weekdays (black dots) and weekend (grey dots) using (a) equal forecast price for both markets and (b) $+75\%$ LM forecast price. As expected, it can be seen that LM clearing prices were higher when the forecast price was $+75\%$ higher than WS market. From the figures we observe that weekend prices are in average lower than those of weekdays. Looking at specific hours, as example we see higher prices in $h = 4$ than those in $h = 12$ or $h = 18$ (weekend and weekdays). This is due to the fact that most MGs have no PV generation at $h = 4$ and that EVs require demand during the night, thus, trades in the LM are needed. Fig. 3(c) depicts supply/demand curves of hours 1 and 23 on two distinct days, i.e. Friday (day 5) and Sunday (day 7) where we can observe variation on the same hour for the selected days. These results show the high diversity of behaviours that could be found in LM. The contributing factor is that players bids and asks have a higher variation compared to WS market.

To summarize, our experimental results highlight that LMs provide an efficient mechanism to reduce costs with the following conclusions.

- If information is received after the WS market cleared a rescheduling needs to be performed which gives an opportunity to trade in LM.
- Accurate clearing price forecasts are needed in order to ensure the ERM models bids accordingly.
- The added value of markets is proportional to cost differences between traders or markets.

VI. CONCLUSIONS AND FUTURE WORK

Current electricity markets lack an integrative approach that efficiently allocates resources between stakeholders of multiple scales (e.g., microgrids, aggregators, large-scale generators). Inspired by diverse projects working on local energy communities, we present an integrated framework that models the problem of ERM, scheduling and bidding in WS and LMs. This provides a short-term balancing market in line with the ambitions of the European Commission. Our case study analyses and highlights the potential benefits of LMs showing improvement with accurate forecasts and when there is a high diversity of traders in the market. The implementation of LM in Europe is still in an embryonic stage, which makes the study of viable alternative models crucial to increase the active participation of consumers. This work explores possible models for LM negotiation considering active consumer participation, in line with the EU guidelines and towards a more flexible power system [8]. Due to the complexity of the matter, several assumptions have been made that may be relaxed in future work. One key limitation of this work is the assumption of consumers being *price takers*,



(a) (b) (c)

Fig. 2. (a) Impact of the success rate for an offer to be accepted in the LM. A clear trend of improvement is observed when the success rate increases. (b) Effect of LM price deviation regarding WS market price. (c) Energy traded in the markets.

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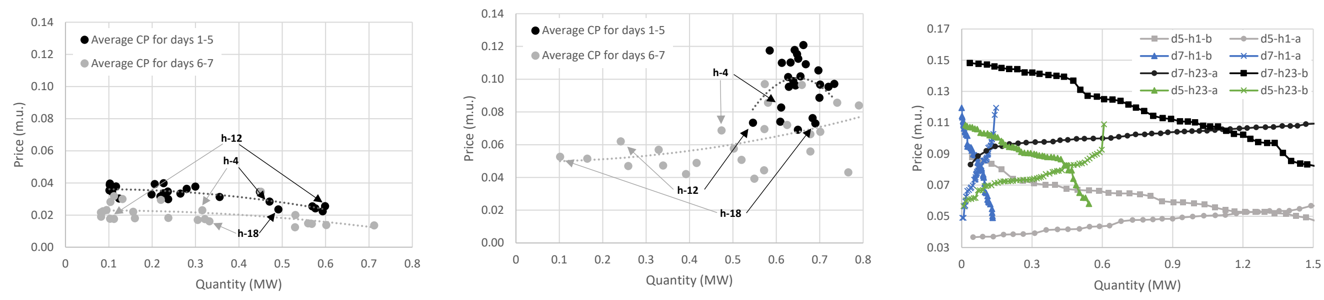

(a) (b) (c)

Fig. 3. Equilibria distribution in LMs for 24 hours on weekdays (black dots) and weekends (grey dots) using (a) equal forecast price for both markets and (b) $+75\%$ LM forecast price; prices on weekdays are higher than on weekends. (c) Supply and demand curves in the LM; comparison of hour 1 on day 5 (grey) and day 7 (blue), and hour 23 on day 5 (green) and day 7 (black); curves show different behaviour for same hours on two different days.

i.e., neglecting the influence of the traded quantity on the price. This assumption is tenable in WS markets but becomes a coarser (albeit common) approximation in LMs. Modelling the *price elasticity* (effect of price on quantity) of the market may provide a competitive advantage to a MG in LMs [22]. In addition, our method may be taken further by learning market and opponent parameters from experience [23], thus reducing the need for prior knowledge and broadening the scope of applicability into more realistic scenarios where agents might change behaviours [24]. The modelling of technical constraints, including power flow validation and network costs in the negotiated prices, is another research avenue. Some works have suggested that when a considerable number of price-sensitive loads is present, maximizing surplus is a preferred objective over minimizing operational costs [25]. Therefore, contrasting our model with such approach will represent another step to achieve practical implementations of LMs.

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