Decision Support for Small Players Negotiations Under a Transactive Energy Framework

Tiago Pinto, Ricardo Faia, Mohammad Ali Fotouhi Ghazvini, Joao Soares, Juan Manuel Corchado, and Zita Vale

***Abstract*—This paper proposes a decision support model to optimize small players' negotiations in multiple alternative/complementary market opportunities. The proposed model endows players with the ability to maximize their gains in electricity market negotiations. The proposed approach is integrated in a multi-agent simulation platform, which enables experimenting different market configurations, thus facilitating the assessment of the impact of negotiation outcomes in distinct electricity markets. The proposed model is directed to supporting the actions of small players in a transactive energy environment. Therefore, the experimental findings include negotiations in local markets, negotiations through bilateral contracts, and the participation in wholesale markets (through aggregators). The validation is performed using real data from the Iberian market, and results show that by planning market actions considering the expected prices in different market opportunities, small players are able to improve their benefits from market negotiations.**

***Index Terms*—Decision support systems, electricity market, local markets, multi-agent systems, transactive energy.**

I. Introduction

With the introduction of renewable energy sources in the energy system, the characteristics of this sector have changed completely [1]. The particularities of renewable generation sources (e.g., intrinsic intermittence and distributed nature) not only have an increasing influence on the electricity network management, but also on the way electricity is traded. With these changes, Electricity Markets (EM) have become more complex and also more competitive. This requires new and effective methods for market operation [1].

In order to deal with the new reality, the concept of Smart Grid (SG) has emerged [2]. SG implementations are growing all around the world [2], [3], managing local generation and consumption independently from the main system. The evolution of the power system towards a transactive energy system, making use of the already made investment in SG and microgrids [4], forces the involved players to adapt to the new reality and seek new ways to potentiate their investments in such a competitive environment.

The new paradigm in power and energy systems and in EM in particular has forced the involved players to rethink their behaviour to be able to cope with the ongoing changes. This need has led to the emergence of several simulation tools [5]. Many of these simulators are based on multi-agent software, as it is a particularly well fitted to analyse dynamic and adaptive systems with complex interactions among its constituents, such as EM [6]–[8]. These simulators are well suited to analyse market and network constraints, hence being particularly relevant for market regulators and operators. However, the perspective of market participants, especially small players, is being highly neglected. There are several works that address the decision support for market players, e.g., from a portfolio optimization perspective [9] and strategic bidding [10], but despite the development in this area, the ability to learn and adapt to provide the best possible results for EM players is still not being properly addressed. In particular, the intelligent use of multiple EM opportunities as they arise is yet relatively unexplored, and should be improved in order to enable players optimizing their participation in several simultaneous EM, including the possibility of negotiating at a local level.

In order to overcome the identified limitations in the field, this paper introduces a portfolio optimization model for small players decision support in multiple EM participation. The considered model considers real-time adaptation to the most recent events and offers the possibility of buying and selling in the same period, in different EMs, including negotiations in local markets. Additionally, real data is used, making the optimization adaptive to the evolution of negotiation contexts throughout the time, by using enhanced market price forecasting. The proposed approach is integrated in AiD-EM (Adaptive Decision Support for Electricity Markets Negotiations) [11], a decision support system for EM negotiations, which enables testing and validating negotiation outcomes through the connection to MASCEM (Multi-Agent Simulator of Competitive Electricity Markets) [6]. MASCEM enables simulating different market models, supporting the experimentation of potential future market scenarios.

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After this introductory section, Section II provides a discussion of the related work in the field, mainly addressing the state of the art regarding the evolution of EM towards local energy markets, leading to a transactive energy environment, and the overview on current decision support solutions for market players' negotiations. Section III describes the market models considered in this work, both for wholesale and local levels. Section IV details the proposed methodology, including the mathematical formulation of the decision support approach, and the multi-agent framework used for EM simulation. Section V presents a case study based on real data from the Iberian EM – MIBEL [12], which validates the proposed approach and compares the achieved results to the outcomes from alternative approaches. Finally, Section VI presents the conclusions and contributions from this work.

II. Related Work

The centralized top-down approach of EM has proven to be insufficient to take full advantage from the participation of small players, and the tentative reforms of retail markets are not being able to achieve the envisaged goals as they are being built under the same top-bottom principles [1]. Electricity prices for small consumers still do not adequately reflect the EM prices and the introduction of flexible tariffs adapted to consumers' needs and behaviours, able to promote and fairly remunerate their contribution towards an increasingly efficient power and energy systems are still distant targets.

New approaches able to bring a closer connection between small consumers and distributed generation and the wholesale EM are required [11]–[13]. A pioneer solution is currently being implemented in New York; the creation of Local EM as part of the Regional EM is being put into practice, enabling smaller portions of the power network (microgrids) to participate in EM as aggregators of the resources that are part of the portion of the grid. Resources can be managed at a local level, enhancing the potential of smaller sized resources, and their participation in EM is facilitated by microgrid operators [14]–[16]. This provides an important incentive for the development of adequate methods to manage resources at lower levels and facilitate their connection with wholesale EM.

The transition towards local EM can be achieved through the emergence of SG, a crucial foundation for the work to be done in the coming years towards the modernization and restructuring of the power and energy sector according to the new paradigms [17]–[21]. This also paves the way for the widespread of transactive energy system [22], by facilitating the full connection from the wholesale EM all the way towards behind the meter. SG and aggregators compose the intermediary layer that chains this connection. Players in local energy communities are able to exchange services and transactions, with the support of specialized players, thus being able to capture market prices at the wholesale level and to profit from opportunities provided by the variation of renewable based generation at local level [23].

Decision support in this domain is, however, still in a very embryonic stage. Local market models are still not sufficiently validated and consolidated, which drives most of the current works into a more conceptual and regulatory nature. In the meanwhile, small players, both consumers and distributed generation, are still facing difficulties in facing market changes and planning their future operation. Most of the works that deal with decision support to market players' actions address the problem from the producers' perspective, as can be seen in [10], which provides a rather complete survey on this subject. The first approaches in this field address the problem using game theory and operational research techniques in order to deal with the considerable data uncertainty that affects agents' decisions in the electricity market, especially when facing multiple market opportunities [24]. The problem of multiple electricity markets participation is approached in [25] by formulating the market bidding problem as a multi-stage stochastic programming model considering sequential electricity markets.

Facing several simultaneous market opportunities drives market participation planning into a portfolio optimization problem. The typical portfolio optimization problem consists in finding the optimum way of investing a particular amount of money in a given set of securities or assets [26]. This is a widely used approach in economics and finance, but its application in the power and energy domain is still rather unexplored. A Genetic Algorithm (GA) is used in [27] to solve the portfolio optimization problem; this paper concludes that GA is an effective method for solving the portfolio optimization problem with different risk measures. Particle Swarm Optimization (PSO) is used in [28] and [29] as an alternative method to solve the portfolio optimization problem. A modification of the portfolio optimization problem is proposed in [30] to incorporate investor's preferences. Meta-heuristic techniques are, in fact, a common choice for the resolution of this optimization problem, as detailed in [31], where a rather complete survey on the use of evolutionary algorithms to handle the portfolio optimization problem is presented.

In summary, most approaches that can be found in the literature present a very economical and financial nature. The resolution of this problem from an EM perspective is rather uncommon, and the existing approaches, such as [9] and [32] make very limitative simplifying assumptions. The influence of the available information (often private) and of the counterparty risk in the outcomes of the portfolio optimization problem (as studied in [33] is often disregarded. The credibility of the risk and return measures [34] is another important, yet, frequently marginalized aspect. Most importantly, specific characteristics that make EM such complex and dynamic environments are completely overlooked [35], such as: the possibility for players to sell and buy electricity in the same period in different markets; the influence of market prices' forecasting error in the risk formulation; the real-time adaptation to the most recent events (e.g., real-time market data); the adaptability to different market scenarios and to different time ranges of optimization; and the dependency of the return price on the negotiated amount, especially in bilateral contract negotiations, where the settled prices are largely dependent on the envisaged trading amount. Such limitations make the current solutions unusable in a real EM environment.

This paper overcomes some of the identified limitations in the state of the art by proposing a novel methodology for the optimization of small players' participation in multiple alternative/complementary markets. The proposed model, being formulated from the perspective of a small player, accommodates the participation in local markets, both at microgrid and SG level, negotiations between neighbour SG/microgids, and also the participation in the traditional wholesale markets, such as day-ahead spot markets, intraday markets, and negotiation by means of bilateral contracts. The considered market models are described in Section III. By implementing the problem from the small players' perspective, the proposed approach enables overcoming the limitations related to the lack of decision support to small players, by focusing the scope of the work on the maximization of small players' outcomes from multiple market negotiations. By including different markets, from different dimensions, the proposed model considers a fully transactive energy system.

III. Market Models

This work addresses players' participation in multiple EM. It is not the objective of this work to propose new models for market mechanisms at the local level, rather proposing a new model to support small players' decisions when facing multiple market opportunities. Hence, the considered market models are based on current market mechanisms used by worldwide market operators. In specific, two types of market mechanisms are considered, namely double auction markets and negotiation by means of bilateral contracts.

A. Double Auction Market

Double auction markets are, currently, the most used market model [1]. They are used by most market operators in Europe for day-ahead spot markets and intraday markets [12], [41], [42]. Double auction based markets comprise bids from both sellers and buyers. Such markets are structured to consider production fluctuations as well as differences in production costs of distinct units. In this market, each participating entity must present their selling or buying proposals for each negotiation period (typically 24 hourly periods of a day in day-ahead markets, but also for different numbers of periods in intraday markets). These proposals or bids are typically composed by a tuple (power, price), with different meanings, whether they come from buyers or sellers, respectively: power stands for amount of power to be bought or sold, and price is the maximum accepted price or minimum selling price. When the negotiation is finished, an economic dispatch for each period is set by the market operator. At the end of each period the market operator uses a market-clearing tool establishing the market price – a unique price that is applied to all transactions in the period.

The market mechanism works as a symmetric market, where both suppliers and consumers submit bids. The market operator orders the selling and demand offers: selling bids start with the lowest price and move up, and demand bids start with the highest price and move down. Then, the proposed bids form the supply and demand step curves, and the point at which both curves intersect determines the market price, paid to all accepted supplier and consumers. The bids of every supplier offering prices lower than the established market price and every consumer offering prices higher than the market price are accepted. Distinct variations of this market type are used by different market operators, e.g., MIBEL accommodates the submission of complex offers [12], Nord Pool supports block orders [36], and EPEX includes the possibility for flexible orders [37].

For simplicity reasons, this work considers a standard symmetrical auction market, without the possibility for submitting special types of offers. In this work, auction based markets are considered for the wholesale day-ahead spot market, for the several intraday market sessions, and also for a local auction market. The local market is assumed to be open to any player located in the geographical area of the respective microgrid or SG. The participation in the wholesale day-ahead market and the intraday market is limited by the player size, which restricts the participation to big players. Hence, the participation of small players is accomplished by means of aggregators, such as the corresponding SG operator.

B. Bilateral Negotiation

Bilateral negotiations are direct negotiations between two players, which may include energy prices and quantity, delivery time and contract duration. Players define contracts' terms and conditions independently from the market operator. Usually bilateral contracts are used to protect players from market's fluctuation prices. Furthermore these contracts are very flexible, since both parts can set the contract terms.

In this work, standard bilateral contracts are considered, in which players agree on a price and amount of energy for a specified time period. Bilateral contracts are considered at several negotiation levels, namely (i) standard bilateral contracts, which can be established between any two players in the market; (ii) local bilateral contracts, which are trading agreements established between neighbour players in the same local operation area (same microgrid or SG), also referred to as Peer-to-Peer (P2P) trading [38]; and (iii) bilateral trading between neighbour SG and microgrids, which are not established by the small players directly, rather by an aggregator, such as the SG or microgrid operator.

IV. Proposed Methodology

The proposed methodology consists of finding a set of actions that make the market share the most advantageous as possible for a supported market player. These actions include the sale and purchase of electricity, which may occur within the same market and time period, depending on the characteristics of each market, including negotiations in local markets. The amount of power that each player should negotiate in each available market type in order to maximize its profits, takes into account the prices that are expected to be achieved in each market, in different contexts. The expected prices in the different market types, at each time are used for an optimization process, which originates the most advantageous participation portfolio. This model is presented in Sub-section A.

The decision support model is integrated in a multi-agent framework composed by different Multi-Agent Systems (MAS), which are specific for distinct purposes, namely electricity market negotiations, microgrid and smart grid modelling, and decision support for players' negotiations, as presented in Sub-section B.

A. Mathematical Formulation

Considering the expected available power of a market player for each period of each day, the amount to be negotiated in each market opportunity is optimized. The formulation presented in (1) is used to represent the optimization problem, aiming at maximizing small players total profits *TP* in EM negotiations.

$$maximize\, TP = I - C \tag{1}$$

where *I* is the total incomes achieved by the small player with the sale of energy throughout the considered optimization period, and *C* stands for the total costs. *I* and *C* are formalized in (2) and (3) respectively.

$$\begin{aligned} I = &\sum_{AM=\mathrm{AM1}}^{NAM} \left(SA_{AM,d,\mathrm{t}} \times FP_{AM,d,\mathrm{t}} \times Asell_{AM} \times M^{open}_{AM,d,t} \right) \\ &+ \sum_{BM=\mathrm{BM1}}^{NBM} \left(SB_{BM,d,\mathrm{t}} \times EP_{BM,d,\mathrm{t}} \times M^{open}_{BM,d,t} \right) \\ &\forall d \in Nday, \forall t \in Nper, Asell_{AM} \in \{0,1\}, M^{open}_{AM,d,t} \\ &\text{and } M^{open}_{BM,d,t} \in \{0,1\} \end{aligned} \tag{2}$$

where d represents the day, $Nday$ is the number of days, t represents the negotiation time period, $Nper$ is the number of negotiation periods, AM and BM represent each auction based market and bilateral negotiation market, respectively. NAM is the number of auction based markets, NBM is the number of bilateral negotiation market. $SA_{AM,d,t}$ represents the amount of power to sell in market AM and $SB_{BM,d,t}$ represents the amount of power to sell in bilateral negotiation market BM. M^{open} is a boolean variable that defines if the market is open or closed, and thus defines if players can participate in that market at each time period. $FP_{AM,d,\mathrm{t}}$ represents the forecasted (expected) market price for selling in each session of each auction based market, in each period of each day. The market price forecasts are executed using an Artificial Neural Network (ANN), which is presented in [39]. $EP_{AM,d,t}$ represents the estimated (expected) price for selling in each bilateral negotiation market. Since the electricity price is highly variable depending on the amount of traded electricity in bilateral contracts, the estimation of expected prices in bilateral contracts is addressed through an estimation methodology based on fuzzy logic and clustering, which is presented in [40]. $Asell_{AM}$ is a boolean variable indicating if the player is allowed to participate in negotiations in each market type, due to the particular restrictions of each market and the characteristics of the player, e.g., dimension, as some markets have a minimum allowed amount for participation, or geographical location.

$$\begin{aligned} C = &\sum_{AM=\mathrm{AM1}}^{NAM} \left(BA_{AM,d,\mathrm{t}} \times FP_{AM,d,\mathrm{t}} \times Abuy_{AM} \times M^{open}_{BA,d,t} \right) \\ &+ \sum_{BM=\mathrm{BM1}}^{NBM} \left(BB_{BM,d,t} \times EP_{BM,d,\mathrm{t}} \times M^{open}_{BB,d,t} \right) \\ &+ \sum_{BM=\mathrm{BM1}}^{NBM} Cost^{TEP}_{d,t} \\ &\forall d \in Nday, \forall t \in Nper, Abuy_{AM} \in \{0,1\}, M^{open}_{BA,d,t} \\ &\text{and } M^{open}_{BB,d,t} \in \{0,1\} \end{aligned} \tag{3}$$

where $BA_{AM,d,t}$ is the amount of power to buy in each session of each market AM and $BB_{BM,d,t}$ is the amount of power to buy in bilateral negotiation market BM. $Abuy_{AM}$ is a boolean variable indicating if the player is allowed to buy in each market type. Besides the constraints related to size and location, several markets also impose rules that only allow seller players to buy in intraday markets, if they have participated in the day-ahead spot market to sell, e.g., in MIBEL [12]. $Cost^{TEP}_{d,t}$ is the generation costs in each period of each day. *TEP* is the total electricity produced, as in (4).

$$TEP \in \{Renew_{prod}, Therm_{prod}\} \tag{4}$$

where $Renew_{prod}$ is the renewable $Therm_{prod}$ the thermoelectric generation. $Cost^{TEP}_{d,t}$ is assumed as null for renewable generation, and as in (5) for thermoelectric power, where a, b and c are the marginal cost coefficients.

$$Cost^{TEP}_{d,t} = a \times Therm_{prod}{}^2 + b \times Therm_{prod} + c \tag{5}$$

The main constraint of this problem is expressed in (6), and imposes that the total electricity reserved to be sold in the set of all markets is never higher than the total expected production *TEP* of the player, plus the bought electricity in all markets in the same time period. The other constraints are more specific for the characteristics of each player; it should be noted that if the player is a thermoelectric generator, it should either not produce at all, or produce at least a minimum value, because it is not possible to operate under a minimum technical limit. Constraint (8) expresses this condition. Further constraints can be added to the problem, particularly of more technical nature.

$$\begin{aligned} &\sum_{AM=AM1}^{NAM} SA_{AM} + \sum_{BM=BM1}^{NBM} SB_{BM} \\ &\le TEP + \sum_{AM=AM1}^{NAM} BA_{AM} + \sum_{BM=BM1}^{NBM} BB_{BM} \end{aligned} \tag{6}$$

$$0 \le Renew_{prod} \le Max_{prod} \tag{7}$$

$$Min_{prod} \le Therm_{prod} \le Max_{prod},\ if\ Therm_{prod} > 0 \tag{8}$$

$$0 \le TEP \le TEP_{max} \tag{9}$$

$$M^{open}_{(AM,\ BM,BA,BB),d,t} = \begin{cases} 0 & o.w. \\ 1 & if\ A^{Trading}_{(SA,SB,BA,BB)} \geq Trading^{min} \end{cases} \tag{10}$$

In restrictions of equation (10), the $A^{Trading}$ refers to the amount that the player will negotiated in the different markets, the $Trading^{min}$ refers to the minimum amount that is possible be negotiated. The variable M^{open} takes the value of 1 if the superiority condition is reached.

$$EP_{BM,d,.t} = Value\left(A^{Trading}_{(SA,SB),d,t}\right) \tag{11}$$

$$EP_{BM,d,t} = Value\left(A^{Trading}_{(BA,BB),d,t}\right) \tag{12}$$

With the application of a clustering mechanism $(Value)$ function in equations (11) and (12) it is possible to apply a fuzzy approach to estimate the expected prices depending on the negotiated amount [40]. Equation (13) defines this condition, where $Data$ refers to the historical data that correlates the amount of transacted power, the day, period of the day and the particular market session. In summary, this estimation is done by applying fuzzy logic on the absolute amount of the power, to classify it in one of the categories defined by a clustering mechanism, which groups the ranges of amounts that present similar prices in each market. The correspondent estimated expected price is then obtained through a data matrix which stores all the expected prices. This estimation process can be consulted in detail in [40].

$$Value\left(A^{Trading}_{(SA,SB),d,t}\ or\ A^{Trading}_{(BA,BB),d,t}\right) = Data(fuzzy\,(pow))_{(AM,\ BM,BA,BB),d,t} \tag{13}$$

The power balance constraint required by the DC Optimal Power Flow (OPF) at all buses of the grid is shown in (14). Constraint (15) enforces the lower and upper bus voltage limitations. Generation of each production unit and the consumption of each load is limited by (16) and (17).

$$P^{DG,t}_b - P^{Load,t}_b = \sum_{CeB_i} \frac{1}{x_{bc}} \left(\delta^t_b - \delta^t_c\right) \quad \forall t \in T, \forall b \in B_i \tag{14}$$

$$\delta^{Min}_b \leq \delta^t_b \leq \delta^{Max}_b \qquad \forall t \in T, \forall b \in B_i \tag{15}$$

$$P^{Min}_g \leq p^t_g \leq P^{Max}_g \qquad \forall t \in T, \forall g \tag{16}$$

$$P^{Min}_l \leq p^t_l \leq P^{Max}_l \qquad \forall t \in T, \forall l \tag{17}$$

where $p^{Load,t}_b$ is the aggregated load at bus *b* and $p^{DG,t}_b$ is the aggregated generation at bus *b*. p^t_g is the active power generation of *g* and p^t_l is the active demand required by load *l*. δ_b is the voltage angle in bus *b*, and $\delta^{Min/Max}_b$ is the minimum/maximum bus voltage. $P^{Min/Max}_g$ is the minimum/maximum power generation of *g*, and $P^{Min/Max}_l$ is the minimum/maximum power consumption of load *l*.

This optimization process allows to:

- Play with the possibility of negotiating in different market opportunities depending on the expected prices at each moment, considering the negotiation amount;
- Play with the possibility of negotiating with neighbours in search for advantageous deals, thus avoiding the need to negotiate solely in regional or wholesale markets;
- Play with the possibility to negotiate with different players in the bilateral contracts, and so having the chance to get higher or lower prices, depending on the circumstances;
- Play with the chance to wait for the later sessions of the balancing market to provide higher amounts of energy, if it is expected for the price to increase;
- Play with the possibility for sellers to buy and buyers to sell in the balancing market, to get good business opportunities: using arbitrage opportunities, buying extra energy when the prices are expected to be lower, and then selling it later when the prices go up; or if the prices show the opposite tendency, offer more energy than the player actually expects to produce, to get greater profit, and then buy that difference in the expected lower prices opportunities.

The proposed model is integrated in the AiD-EM decision support system, which enables re-executing this methodology every time a transaction in a certain market occurs. This enables the small player to re-plan its actions after each agreement, and thus always re-schedule the negotiation plan according to the most recent perceived events and most updated forecasts.

B. Multi-Agent Architecture

1) AiD-EM: The proposed negotiation portfolio optimization model is integrated in AiD-EM [11], a multi-agent decision support system that enables electricity market players to use the available data in an intelligent and adaptive way in order to cope with the multiple challenges that arise from EM participation.

AiD-EM uses real market data, data derived from past and current simulations, and external sources data (e.g., weather conditions such as wind speed, solar intensity and temperature; or raw materials prices, among other) to support the decision making process. Decisions are modelled specifically for each different market negotiation type, namely the negotiation of bilateral and forward contracts, and participation in auction based markets, such as the day-ahead spot market and balancing markets. The multi-agent approach of AiD-EM facilitates the interactions between the different components and also the communication with external agents, such as the market players themselves, which make use of the decision support. Fig. 1 presents the multi-agent architecture of AiD-EM, including the portfolio optimization model.

As shown by Fig. 1, the AiD-EM Manager agent is the main entity of the system, detaining the responsibility of providing the connection with the MASCEM electricity market simulator through the direct interaction with the supported market player(s). When several market players require the decision support of AiD-EM simultaneously, multiple AiD-EM Manager agent instances are created, so that each supported market player has its own Manager agent, with the sole responsibility

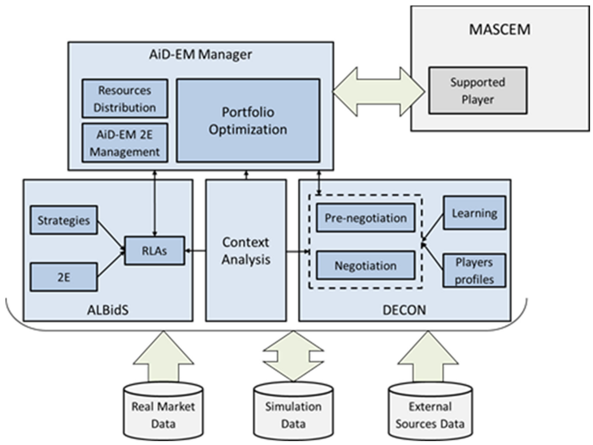

Fig. 1. AiD-EM multi-agent architecture, adapted from [11].

of handling the player's decision making process. For this, the AiD-EM Manager agent executes the portfolio optimization methodology, presented in Section 3.1, in order to decide whether and when the supported market player should participate in each market type. Once the objectives for each market participation are defined, ALBidS (Adaptive Learning Strategic Bidding System) [41] is used to support negotiations in auction based markets, e.g., spot and intraday markets. When the negotiation by means of bilateral negotiations is also envisaged, the DECON (Decision Support for Energy Contracts Negotiation) system is used [42].

The connection to MASCEM enables testing and validating the developed decision support methodologies under realistic simulation conditions, taking advantage on the enhanced simulation capabilities of MASCEM and on the interactions between the involved players.

2) MASCEM: MASCEM [6], [13] provides a simulation platform for the study of complex electricity markets. MASCEM allows the simulation of the main market models: day-ahead pool (asymmetric or symmetric, with or without complex conditions), bilateral contracts, balancing market, forward markets and ancillary services. Hybrid simulations are also possible by combining the market models mentioned above. Also, the possibility of defining different specifications for the market mechanisms, such as multiple offers per period per agent, block offers, flexible offers, or complex conditions, as part of some countries' market models, is also available. Some of the most relevant market models that are fully supported by MASCEM are those of the Iberian electricity market – MIBEL, central European market – EPEX, and northern European market – Nord Pool.

Simulation scenarios in MASCEM are automatically defined, using the Realistic Scenario Generator (RealScen) [43]. RealScen uses real data that is available online, usually in market operators' websites. The gathered data concerns market proposals, including quantities and prices; accepted proposals and established market prices; proposals details; execution of physical bilateral contracts; statement outages, accumulated by unit type and technology; among others. By combining real extracted data with the data resulting from simulations, RealScen offers the possibility of generating scenarios for different types of electricity markets. Taking advantage on MASCEM's ability to simulate a broad range of different market mechanisms, this framework enables users to consider scenarios that are the representation of real markets of a specific region; or even consider different configurations, to test the operation of the same players under changed, thoroughly defined scenarios.

3) MASGriP: The modelling of players at the microgrid level is provided by MASGriP, which simulates, manages and controls the most relevant players acting in a smart grid environment [44]. This system includes fully simulated players, which interact with software agents that control real hardware. This enables the development of a complex system capable of performing simulations with an agent society that contains both real infrastructures and simulated players, providing the means to test alternative approaches (energy resource management algorithms, demand response, negotiation procedures, among many other) in a realistic simulation environment [45].

MASGriP provides a simulation platform that allows the experimentation and analysis of different types of models, namely energy resource management methodologies, contract negotiation methods, energy transaction models, and diverse types of DR programs and events. The simulated players in MASGriP have been implemented to reflect the real world. These players include some operators, such as the Distribution System Operator (DSO) and the Independent System Operator (ISO). However, the majority of players represents energy resources, such as several types of consumers (e.g., industrial, commercial, residential), different types of producers (e.g., wind farms, solar plants, cogeneration units), EVs with vehicle-to-grid capabilities, among others. Aggregators present an important role in the future power system management and operation. Some examples of the considered aggregators are: Virtual Power Players (VPP) [16], which can aggregate any other resource, including other aggregators; Curtailment Service Providers (CSP), which aggregate consumers that participate in DR programs; smart grid and microgrid operators, which manage the players that are contained in a specific area. These players introduce a higher level of complexity in the system management. MASGriP's interaction with MASCEM and with AiD-EM creates an enhanced modelling and simulation framework that facilitates the study of a large diversity of scenarios, providing the means for analysing the interactions between different players of very distinct natures, and assessing the impact of alternative types of management and negotiation.

V. Experimental Findings

Using the integrated multi-agent society, some simulations are executed with the aim of validating the proposed methodology and assessing the impact of using the proposed model for decision support of small players' negotiations in a competitive market environment.

A. Characterization

Simulations are undertaken concerning 1 day with 24 hourly negotiation periods. A total of seven markets are considered,

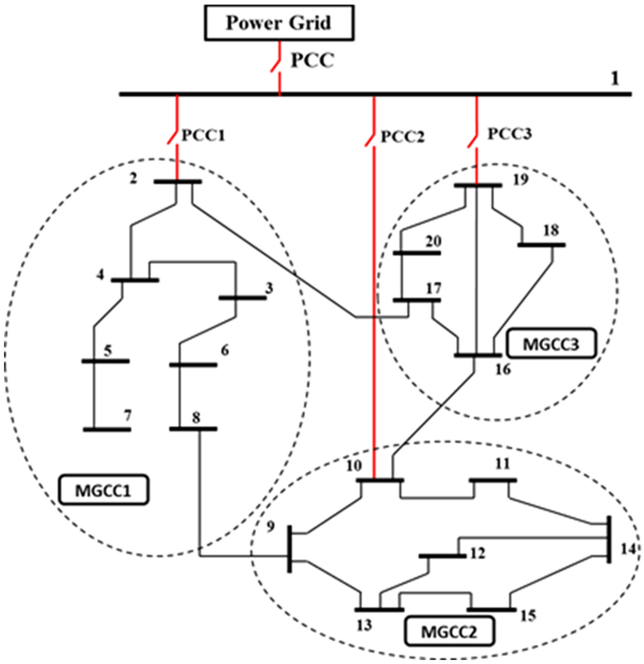

Fig. 2. Integrated microgrids, from [46].

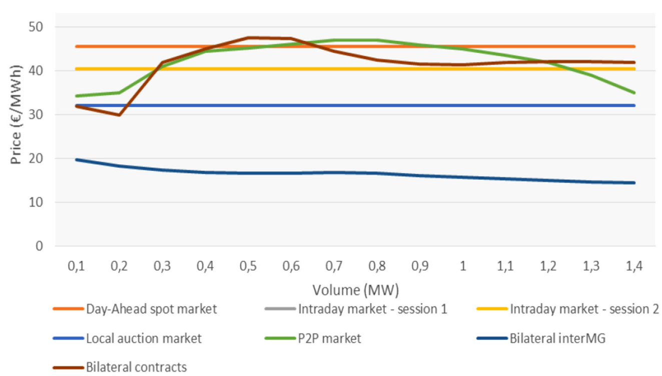

Fig. 3. Expected price variation in the different markets, according to the negotiation amount.

namely four auction based markets: day-ahead spot market, two negotiation sessions of the intraday market and a local auction market, at the microgrid level; and three bilateral negotiation markets: local trading, exclusive to players of the same microgrid, trading between neighbour microgrids, and the typical floor for bilateral contracts, open to any player. These markets follow the rules defined in Section III, and real data is used from MIBEL [12], regarding the day-ahead, intraday and bilateral markets, referring to 1 March, 2017. The prices and players data regarding local markets refers to previous studies, namely from [46], where a test system considering three microgrids is considered (Fig. 2).

The subject player for this case study is a seller (thermoelectric generator), located in MGCC1, with a TEP of 0.4 MW. A limit of 0.4 MW is also imposed as the maximum amount allowed to be purchased in each market. Fig. 3 shows the expected variation of electricity prices in the different considered market

TABLE I
SCHEDULING OF SALES AND PURCHASES IN THE DIFFERENT MARKETS

	Sales (MW)	Purchases (MW)
Day-ahead spot market	1.093	0
Bilateral contracts	0.6499	0.3000
Intraday session 1	0	0.4
Intraday session 2	0	0.4
P2P market	0.8566	0.2999
Bilateral inter-MG	0	0.4
Local auction market	0	0.4

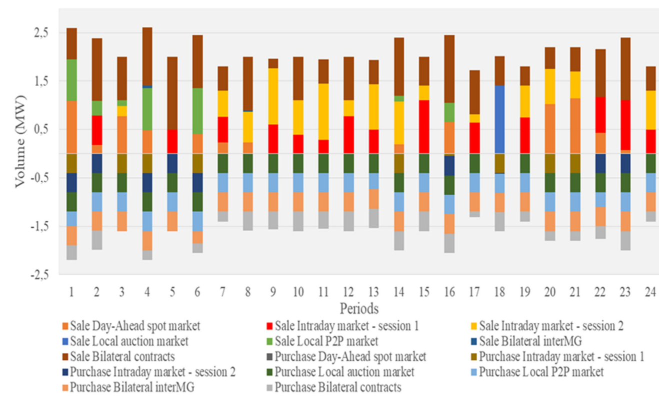

Fig. 4. Scheduled sales and purchases in all considered market for the 24 periods of the simulation day.

types, depending on the traded amount, for the first period of negotiation, as result of the forecasting (for auction based markets) and estimation (for bilateral negotiation markets) processes.

As can be seen from Fig. 3, some markets (day-ahead spot and intraday market sessions) present a unique market price for this hour, regardless of the amount that the supported player negotiates. On the other hand, in the three bilateral negotiations markets, expected prices are variable, depending on the envisaged negotiation amount. Further details on the data used on this case study can be consulted in [47].

B. Results

Table I shows the scheduling of sales and purchases made in the different markets, as result of the proposed optimization process for period 1.

By matching Table I and Fig. 3 it is possible to see that the model presents a solution with the purchased energy in the cheapest markets and sales in the most profitable. As the total energy that can be bought in each market is 0.4 MW, the maximum amount is bought in both intraday market sessions (lower prices than the day-ahead spot market), in the local auction market and in bilateral negotiation with neighbour microgrids. A purchase of approximately 0.3 MW is also allocated to bilateral contracts and to the local P2P market. In these markets, the allocated amount is not the maximum possible volume because, as visible from Fig. 4, the expected tendency in both these markets is for lower prices in amounts below 0.4 MW. The sale of 0.6499 MW is set to bilateral contracts, as this volume represents a peak of expected price, and 0.8566 MW are allocated to local P2P

TABLE II
COMPARISON OF RESULTS WITH OTHER APPROACHES

	Proposed approach	Day-ahead spot market	Previous work (microgid LMP)
Total profit (€)	1,230.723	466.58	363.997

markets for the same reason: higher expected price. The remaining amount of 1.093 MW is allocated to be sold in the day-ahead spot.

Fig. 4 shows the allocated volume for sale and purchase in the considered markets throughout the 24 hours of the considered simulation day. The positive values represent the sales and negative values are the purchases.

The total profit (objective function value) achieved by the proposed methodology in the total of the 24 hours of the considered day is presented in Table II, and compared to the total profit achieved in negotiations when: (i) negotiating the total amount in the day-ahead spot market, which is the traditional negotiation means, where the great majority of electrical power is typically traded; (ii) assuming a centralized management by the microgrid operator, scheduling the microgrid resources, and selling the surplus and buying the lacking amount from the day-ahead market, as in the previous work using these exact microgids data [46]. Details on these prices can be consulted in [47].

From Table II it is visible that the total expected profits from the small seller player when using the proposed approach as decision support for market negotiations planning, is much higher than when considering only the sale in the day-ahead spot market, and when considering the management from a microgrid operator. The proposed approach enables the small player to identify the most advantageous negotiation opportunities in each moment, and includes the possibility of the player to buy extra amount of energy at lower prices, and sell it in opportunities where the expected prices are higher, thus enabling the achievement of higher profits. Regarding the centralized management of the microgird, as discussed in the introductory and related work sections, the models found in the literature typically consider the perspective of the operator/aggregator/manager, and thus aim to maximize the gain of the network. This is, however, contradictory to the interests of the small distributed generators, since the aggregator aims to achieve energy at the lowest possible prices, while the generator aims to sell it at as higher prices as possible. Thereby, models such as the methodology proposed in this paper are essential to balance the conflict of interests, and provide small players with the possibility of improving their outcomes from negotiation and also increase the profitability of investing in distributed generation sources.

VI. CONCLUSION

This paper proposes a decision support methodology for small players, to enable identifying the most advantageous expected negotiation opportunities, and maximize their gains from market negotiations, including the possibility of negotiating in local energy markets. The proposed approach is integrated in a multi-agent simulation framework, which enables testing the model under scenarios based on real data. Results show that the proposed approach is able to allocate the sale of energy to the markets with higher expected negotiation price, and purchases in opportunities of lower prices. Thereby being able to increase the potential profits of the supported small player when considering several alternative / complementary markets, including the negotiation in local markets.

As future work, a risk factor will be included in the proposed model, in order to balance the profit with the participation risk in each market. This risk will be formulated based on the uncertainty resulting from the variability of prices in each market. Moreover, the model will be expanded to include further negotiation opportunities, such as the participation in derivatives markets, contracts by options, and other opportunities resulting from small players association to different types of aggregators.

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