smart cities

Article

Management of Local Citizen Energy Communities and Bilateral Contracting in Multi-Agent Electricity Markets

Hugo Algarvio

LNEG—National Laboratory of Energy and Geology, 1649-038 Lisbon, Portugal; hugo.algarvio@lneg.pt

Abstract: Over the last few decades, the electricity sector has experienced several changes, resulting in different electricity markets (EMs) models and paradigms. In particular, liberalization has led to the establishment of a wholesale market for electricity generation and a retail market for electricity retailing. In competitive EMs, customers can do the following: freely choose their electricity suppliers; invest in variable renewable energy such as solar photovoltaic; become prosumers; or form local alliances such as Citizen Energy Communities (CECs). Trading of electricity can be done in spot and derivatives markets, or by bilateral contracts. This article focuses on CECs. Specifically, it presents how agent-based local consumers can form alliances as CECs, manage their resources, and trade on EMs. It also presents a review of how agent-based systems can model and support the formation and interaction of alliances in the electricity sector. The CEC can trade electricity directly with sellers through private bilateral agreements. During the negotiation of private bilateral contracts, the CEC receives the prices and volumes of their members and according to its negotiation strategy, tries to satisfy the electricity demands of all members and reduce their costs for electricity.

Keywords: agent-based consumers; alliance formation; bilateral contracts; Citizen Energy Communities; electricity markets

check for updates

Citation: Algarvio, H. Management of Local Citizen Energy Communities and Bilateral Contracting in Multi-Agent Electricity Markets. *Smart Cities* **2021**, *4*, 1437–1453. https://doi.org/10.3390/smartcities4040076

Academic Editor: Alessandro Burgio

Received: 28 October 2021
Accepted: 19 November 2021
Published: 27 November 2021

1. Introduction

Traditionally, the organization of the electricity sector was based on vertically integrated companies of the power sector, which produced, traded, transported, and distributed energy without any competition. Liberalization began in the earlier nineties, separating the roles of production and trading from the natural monopoly roles of transmission and distribution [1]. This process has led to the establishment of a wholesale market, where competing producers offer their energy to retailers, and a retail market, where retailers satisfy the needs of end-users [2,3]. Market forces now determine the price of energy and reduce net cost through increased competition. Also, end-users can freely choose their energy providers based on the best tariffs [1–6]. The participants in electricity markets (EMs) are heterogeneous, autonomous, and follow their own goals and negotiation strategies. Usually, production companies seek to adopt strategies that maximize profit, while consumers adopt strategies that minimize electricity costs. Most strategies help negotiating parties to reach mutually beneficial agreements [2,3,6].

Three major market models are often distinguished [7,8]: spot, bilateral contracts, and hybrids models. A spot market is a centralized marketplace that clears the market for sellers and buyers. Power system sellers/buyers submit bids to the pool for the quantities of energy that they want to trade in the market. The bids are submitted to a market operator, whose function is to coordinate and manage the different transactions between the participants. Bilateral contracts are negotiable agreements of energy between two traders. These contracts have the advantage of price predictability in comparison to uncertain pool prices. The hybrid model considers several characteristics of the previous two models. In this model, a spot market is not mandatory, and customers can either negotiate energy directly with suppliers or at the power exchanges [1]. There are several procedures for bilateral contracting of electricity, notably the alternating offers and the contract net procedures. The former involves only two parties and focuses on an iterative exchange of offers and counter-offers. The contract net protocol involves typically a trader and several opponents, e.g., a buyer sends a call for proposal (quantities of electricity) to several sellers who reply by sending specific energy prices [9].

Decision making becomes very difficult in EMs because of their complexity and high uncertainty, which increased in the last few decades. Recent changes in the electricity sector have come to prove that the demand-side may also have a relevant influence on the whole process, especially regarding strategic decisions made by end-users. In this new paradigm, consumers and buyers of energy can play a much more active role in EMs and, through appropriate strategies, achieve their objectives. However, EMs still present limitations, such as the exclusive participation of very large players [5,10]. Furthermore, there is a practically exclusive participation of producers in the ancillary services of power systems [4–6]. In order to overcome these limitations, end-users can form alliances. Furthermore, alliances of two or more end-users can significantly increase their negotiating power during bilateral negotiation of electricity [11,12].

A Citizen Energy Community (CEC) is an alliance that can be composed of several power system actors, such as consumers, prosumers, electric vehicles (EVs), storage facilities, generators, aggregators, and system operators of a local area [12–14]. The legislation of diverse countries of the European Union (EU) incentivizes the formation of CECs with self-consumption by providing discounts to some fixed taxes of the variable term of the electricity tariff [12,15]. Besides these discounts, CECs can also have enough weight to be active market players, participating in spot and derivatives markets, but also negotiating private bilateral contracts. Furthermore, they (potentially) can participate in ancillary services, supporting system operators in balancing the power system and avoiding grid congestions [16]. By forming alliances, such as CECs, power system agents can increase their benefits by having the possibility of participating in several market products to trade electricity or provide flexibility [17]. Power systems with increasing levels of variable renewable energy sources (VRES) increase the uncertainty of the net load, and the need to use ancillary services, guaranteeing power system stability. Currently, very fast-responsive dispatchable power plants, such as natural gas, support the ancillary services, which are becoming very costly [16]. CECs can provide the required flexibility to support the ancillary services of carbon-neutral power systems at reasonable costs [17].

Taking into account the increasing complexity of EMs and limitations in existing simulation tools, this paper describes the potential of agent-based technology to develop a system for bilateral contracting and supporting alliance formation and management. Alliances of consumers are equipped with decision making and team strategies to facilitate managing the complexity of EMs. Specifically, the purpose of this paper is threefold:

(1) To review agent-based alliances in the electricity sector;
(2) To present and test a model for the formation and management of CECs;
(3) To present and test a model for bilateral trading of electricity between CECs and opponents (e.g., producers, retailers, etc.).

Software agents have been developed using the Java programming language and the JADE multi-agent platform [18]. JADE is an agent-oriented platform offering a framework for multi-agent system (MAS) development and it can consider several agent models; Agent communication is done by sending and receiving messages. This paper builds on previous work in the area of multi-agent electricity markets. In particular, it updates the material presented in [19–21] by formalizing the formation of alliances, and [12,22–24] by formalizing a negotiation and decision making model for alliances.

The remainder of the paper is structured as follows. Section 2 presents how power system alliances have been integrated into multi-agent systems. Section 3 presents an overview of a negotiation model for alliances. Section 4 presents a case study. Finally, Section 5 presents the conclusions.

2. Power System Alliances in Multi-Agent Systems

Hunt and Shuttleworth [25] propose four models to chart the evolution of the electricity supply industry towards full competition: regulated monopoly, purchasing agency, wholesale competition, and retail competition (see also [1]). Due to increased competitiveness and dynamism, the electricity sector is very exposed to external changes. Thus, it is very important to support all involved players in this complex environment. Presently, there are various simulation systems based on multi-agent technology that allow modelling competitive EMs. Such systems allow market participants to simulate the negotiation of prices and quantities through bilateral contracts, the trade of energy in spot markets, etc. However, they have limitations, mainly because of the complexity of power systems.

There are several simulators using agent technology for simulating actual and future market designs, such as AMES (Agent-based Modelling of Electricity Systems) [26], EMCAS (Electricity Market Complex Adaptive System) [27], GAPEX (Genoa Artificial Power Exchange) [28], MASCEM (Multi-Agent Simulator of Competitive Electricity Markets) [29,30], SEPIA (Simulator for Electric Power Industry Agents) [31] and MATREM (for Multi-Agent Trading in Electricity Markets) [32]. Other simulation tools, which are not agent-based, can also deal with EMs, such as Power Web [33], and SREMS (Short Medium run Electricity Market Simulator) [34]. AMES is an open-source MAS developed with the JAVA language, for the Repast platform, and involves four main components: traders, transmission grids, markets (day-ahead and real-time), and an independent system operator (ISO) with four functions, namely system reliability assessment, day-ahead unit commitment, dispatch, and settlement [26]. Repast is a free, open-source, agent-based modelling and simulation toolkit that can be used for several applications [35]. EMCAS supports negotiation through bilateral contracts and pool markets, and includes agents representing producers, intermediaries, consumers, and ISOs. The agents are autonomous and perform decisions based on expected prices for pool and bilateral contracts, obtained through historical analysis and future predictions [27]. GAPEX is implemented in MATLAB. It models and simulates artificial power exchanges replicating the market-clearing techniques of the most important European markets [28]. MASCEM includes agents that can simulate market facilitators, generators, consumers, market operators, traders, and system operators. It features bilateral contracts and a pool market, where accepted agreements must be submitted for verification by the market operator [29,30]. SEPIA is a tool for developing EM models with the purpose of gaining insights into the behaviour of its participants and their impact on EMs. It only allows bilateral contracting, where agents (composed of diverse layers) are as follows: grid zones, generators, GenCos, generator of last resort, consumers, consumer companies, transmission grid, and system operator [31]. MATREM effectively supports market players in their key decisions related to the power systems of the future (i.e., involving high levels of renewables and alliances) [32] and is composed of agents capable of adapting to different market contexts and by various market models, supporting market participants in their complex decisions [8]. The architecture, characteristics, and capabilities of these agents can be found in [36]. MATREM is composed of consumers, coalitions of consumers, producers, aggregators, retailers, and system and market operators. MATREM can simulate day-ahead and intraday markets considering zonal and nodal marginal pricing. It also allows trading on derivatives markets, mainly forwards, futures, and contracts for differences [37]. Furthermore, it also allows the negotiation of private bilateral contracts. It is also equipped with secondary and tertiary balancing markets and with an imbalances settlement algorithm that computes imbalance prices [16]. Power Web allows to test and analyse different kinds of energy markets, but only supports fixed demand for pool markets [33]. SREMS is based on game theory and supports scenario analysis in the short–medium term. It evaluates the transacted power, but was designed only for the Italian EM [34].

The majority of existing tools focus on the following types of entities:

- GenCos or generators—represent utility companies or single generators and operate in a wholesale market;

- Traders—promote liberalization and competition, and simplify dealings either between sellers/buyers and the market operator or between sellers and buyers. Some traders can act as speculators in EMs.
- Consumers—represent end-use customers and operate in a retail market;
- System operator—maintains the system security, administers transmission tariffs, coordinates maintenance scheduling, and analyses the technical feasibility of all negotiated contracts;
- Market operator—regulates pool negotiations, and thus, is present only in a pool or hybrid market; uses a market-clearing tool, typically a standard uniform auction, to set market prices.

There are, however, other agents that play an important role in electricity markets, but are not modelled by the majority of these tools, notably:

- Regulator agents—represent the agents that regulate transmission, distribution, last resource supply, management of markets and, in some cases, approves the rules for bilateral negotiation in the non-organized (sub-) markets;
- Aggregators—manage groups of players of the electricity market (currently these agents are commonly used to manage groups of renewable producers);
- Retailer or supplier agents—represent electricity retailers and operate in both a wholesale and a retail market.

Also, there are some alliances that are emerging and have been modelled only in the past few years, such as:

- Coalition of consumers—represents a set of end-users and, in addition to the role of negotiating bilateral contracts in a retail market on behalf of these consumers, if the coalitions are large enough, they may also trade energy directly in the organized market.
- Virtual power plants—responsible for managing alliances of producers (including the responsibility of negotiating on behalf of such coalitions);
- Virtual power player (VPP)—responsible for managing a set of different technologies, such as power plants, distributed generation, energy storage systems, prosumers, and consumers, considering demand response programs.
- CECs—responsible for managing a set of supply and demand distributed resources, such as distributed generation, consumption, and storage. Normally, these resources are located on the local distribution grid of electricity, with the CEC bearing the responsibility for the electricity trading required by its members.

An alliance is a set of self-interested autonomous agents that can negotiate different items rationally [38]. In Sandholm and Lesser [11] the authors conclude that, generally, by forming an alliance, the agents can sometimes save costs compared to operating individually. In EMs, an alliance of consumers could surpass dimension limitations and directly buy electricity in the pool market or increase its negotiation power, achieving better electricity tariffs while negotiating with retailers. The literature contains a richness of approaches about the aggregation of electricity players [38], giving special attention to production issues, with works about Virtual Power Plants [39,40], Virtual Power Producers [41], and Virtual Renewable Power Plants [42,43]. Concerning consumers, the literature has some references about aggregating and managing consumers [44–46] and their effects [47,48] with special emphasis to prosumers [49–51], the aggregator agent [52], to the VPP concept [30,53], as well as to CECs [12], consumer coalitions and alliances [22–24,54–60].

The aggregator is the operator that manages the aggregated consumers in order to gather flexibility and generate bids to the electricity market. It has the objective of maximizing its revenue. Compared to the aggregator, the coalition and CEC agents aim to minimize its members' tariffs as opposed to the aggregator whose interest is normally only about its own benefit. Prosumers are consumers with production and/or storage capacity, depending on their net load, i.e., load minus local production. VPPs are entities that aggregate different types of technologies. A VPP with several miscellaneous clients with different technologies, manages its portfolio of clients to maximize its revenue, which has a completely different purpose when compared to a CEC. In Hamalainen et al. [44] the authors developed a model where a coalition of cooperative consumers responds to real-time pricing with heating control, to maximize their benefit. In Hatami et al. [45], the authors demonstrate how cooperative networked consumers considering a single electricity bill and dynamic electricity pricing could minimize their bill by reducing the consumption in peak hours. This approach focuses on demand-side management of cooperative consumers that respond to dynamic electricity pricing to minimize their electricity costs. In [12], is presented the benefits of CECs where local consumers and prosumers can form alliances, being members of the CEC, investing in local RES and storage, and establishing bilateral agreements with local big producers, retailers, aggregators, and system operators. By forming alliances and negotiating with other market players, the CEC has the potential to substantially reduce its members' cost for electricity, supporting the investments in DG, and incentivizing carbon-neutrality and energy sustainability. VRES and demand-side players have uncertain power profiles, which increase the uncertainty of the net load. The real-time difference between demand and supply has to be balanced in the ancillary services, which usually have high costs. These costs are passed to the imbalance players, originating penalties. The aggregation of these local players and storage solutions in a CEC may bring the flexibility that future power systems with near 100% RES may need to be economically efficient [46]. This flexibility is also important for CECs to manage the imbalances of their members, reducing their payment with penalties.

Concerning alliances in general, there are important pieces of work on alliance formation [38,43,45], team strategies [54], team decision, and team negotiation models [56–59]. Klusch et al. [38] studied the impact of dynamic coalition formation (DCF) of autonomous agents, taking into account environment and information. They designed a DCF scheme based on simulation (DCF-S) that tries to obtain the best solution (alliance) for every agent. Pinto et al. [43] presented a new model for creating and managing virtual power producers, including a facilitator to manage communications between agents and a mechanism to rank possible agents to join coalitions. Baeyens et al. [54] presented a model for alliances of wind power producers (WPPs) to submit bids to pool and forward markets. They found that alliances of WPPs improve their expected profit. Sanchez-Anguix et al. [55] studied the impact of the negotiation situation over various intra-team strategies: representative (RE), similarity simple voting (SSV), similarity boarda voting (SBV), and full unanimity mediated (FUM). In RE, team members delegate team decision making to a representative mediator. SSV relies on voting procedures and majority rules in each round of negotiations to determine if an opponent's offer should be accepted or not, and which offer is submitted to the opponent. SBV is based on rank proposals. This voting procedure has the advantage of choosing largely accepted proposals rather than majority proposals. In FUM, all members have to agree with all team decisions. They concluded that RE is the faster strategy, but FUM is the strategy that brings higher utilities. Team deadline is critical because when it is shorter than the deadlines of opponents, the team's utilities are negatively affected. Otherwise, if it is longer, negotiations may fail (in case of selecting tough strategies, as FUM). One interesting result is that an increase in the number of team members negatively affects utilities, therefore, the goals, context, and formation of coalitions are very important. The selection of key members is a critical issue to increase utilities. Ephrati and Rosenschein [56] used the Clarke tax mechanism [60] as an economic decision process for having a consensus in MAS. This mechanism has some advantages, such as non-manipulability, individual rationality, and maximization of agent global utility, but it is difficult to implement. Sanchez-Anguix et al. [57] presented a negotiated model for coalitions of consumers negotiating with their opponents and reaching unanimous agreements by using a trusted mediator. They concluded that by achieving unanimous decisions the model can increase the utility of each member concerning its goals. Sanchez-Anguix et al. [58] presented a negotiation model to obtain efficient agreements with low computational costs, concluding that their model can beat similar heuristics with partial information and obtain similar results in the case of full information. Sanchez-Anguix et al. [59] presented a study about the use of bottom-up approaches to achieve Pareto optimal deals when team groups are negotiating, confirming their theory with the achievement of Pareto optimal deals.

Compared with the literature, power system alliances can consider a slightly different interaction process between the mediator and the alliance members. A representative mediator with individual decision making (RM-IDM). Whenever the mediator receives an offer from the opponent's agent, at a specific period, it prepares a new offer and starts a voting process among all members, where both offers are made public. The votes can be positive (acceptance of the opponent's proposal, and consequent rejection of the alliance's proposal) or negative in the case where the alliance's proposal is better than the opponent's proposal. The decision depends on the utilities that each proposal gives to each member of the alliance. Thus, each member receives both proposals, rates them using its utility function, and votes accordingly. The votes are sent to the mediator, who sums up the number of positive votes and makes a decision based on the selected decision rule. Thus, in the case of a majority decision rule, if the number of positive votes is higher than the number of negative votes, then the opponent's offer is accepted and negotiation ends successfully in an agreement. Otherwise, if the mediator and the alliance members decide to continue negotiating, the mediator submits a new offer to the opponent's agent.

Considering coalitions of consumers, in [22], a strategy for retailers to deal with different consumers and coalitions was introduced. A case study was presented, where the strategy was used together with the adaptation of existing intra-team strategies, such as representative and SSV strategies. The case study illustrated that by making alliances and forming coalitions, consumers can increase their bargaining power and achieve more beneficial agreements, obtaining more competitive tariffs. In [23], a slight modification of the interaction process between a trusted coordinator agent and the coalition members was introduced together with a case study. A RM-IDM strategy was considered. Using this particular strategy, all members can vote on their preferred proposal. The mediator presents to all members the proposal sent by the seller and its proposal. The members will vote for the acceptance of the sellers' proposals or for sending a new proposal (the mediator's proposal). The decision can be made over a majority (where more than fifty percent of the coalition members must agree), a consensus (75% must agree) or an unanimity (100% must agree) rule. The strategy was used in a real-world case study, where real consumers and data were used. The results showed that when all coalition members agree (unanimity rule), it is possible to achieve better agreements for all coalition members. In [24], the authors extended the previous two pieces of work by considering a new study with coalitions formed by real schools in the United Kingdom with different sizes, which allows verifying that schools with lower consumption of electricity can benefit by making alliances with schools with higher consumptions, obtaining more competitive tariffs. This paper also tested the selection of a mediator and its consequences. It was verified that independent of the size of each member, and since the mediator negotiates on behalf of the entire coalition, it should be carefully chosen to increase the coalition benefit.

The literature has several approaches concerning supply-side alliances, some works about consumer alliances, and a few works concerning emerging local alliances. CECs can be very important for future carbon-neutral societies, by: (i) using self-consumption, (ii) supporting sector coupling and electrification, and (iii) having enough flexibility to participate in ancillary services and avoid grid congestions.

3. A Negotiation Model for Power System Alliances

Figure 1 shows the common structure of an alliance in general. The agents start forming alliances when they have a common goal, then they start interacting with each other, negotiating, and could achieve an agreement [61,62]. In all phases before signing a contract any member can withdraw from the alliance and also new members could join the alliance [63,64]. The main issue to start a promising alliance is that all members must have a common goal and similar objectives. Then, depending on the alliance type, if all members or their companies do not have any legal relation (belong to the same owner), the formation phase could be started by a founder or a group of founders' members [65].

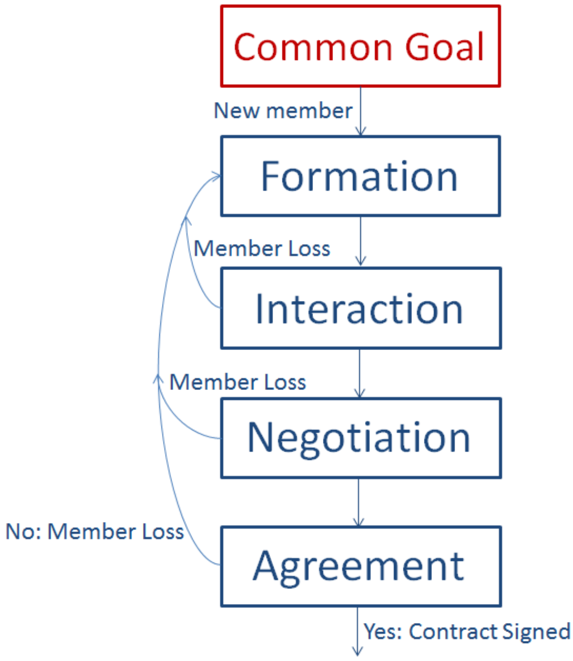

Figure 1. A model for the formation of alliances.

3.1. Formation

The easiest way to form alliances is the aggregation of several desegregated units (buildings, storage, DG, etc.) that have only one management owner [64,65]. In this case, each desegregated unit can be considered a dependent member of the alliance, as a single software agent or be part of an aggregated agent, that manages all units. In case of being dependent agents, they cannot compute their own proposals, accept proposals, or even leave the alliance if their owner does not do it. Their owner or the aggregated agent, can vote for the acceptance of the proposal, propose its own proposal, and leave the alliance. This is the case of a company, country, state or municipal government, other owners of several desegregated buildings or DG (each could be individually considered as a customer or negotiation agent). In those cases, the buildings have different tariffs negotiated by the local or central management of the building or building owner (company, state, etc.). Verifying that the buildings have different tariffs (some better than others) the building owner (an alliance agent) could decide for the aggregation of all building consumption and start negotiating with retailers a tariff that minimizes its electricity costs. If the alliance has enough weight, instead of negotiating with a retailer, it can directly negotiate with producers or participate in electricity markets.

Another way of alliance formation is the sectored aggregation (i.e., the aggregation of the same type of member). This is commonly used by differentiated cooperatives (bankers, loggers, local village, metallurgy, etc.), condos, citizen councils that fights for the citizens' rights, among others. In this type of alliance although the members are independent, normally, not all have the negotiation capacity, and because of that, the negotiation is made by representability, by one of the members or a negotiation expert (for example a company specialized on it), and the members can only accept or not the proposed tariff.

One more complex type of alliance is when the members are different, considering that consumers have the objective of reducing the tariff and producers want to increase profit. Even consumers are different, and to minimize costs, for differentiated tariffs they could prioritize the different items of the tariff (period of the day for example) differently. In a three periods tariff (e.g., 12 p.m.–8 a.m., 8 a.m.–4 p.m. and 4 p.m.–12 p.m.) a commercial agent could give a higher priority to the second period of the day (e.g., 8 a.m.–4 p.m.)

while a domestic consumer will prefer the third period. In this type of alliance, the negotiation between members is more complex, and to maximize the utility for all members and consequently, the alliance's utility, it is beneficial that most members have active participation in the negotiation process, instead of having a representative negotiating for them, such as in the other simpler types of alliances presented earlier [64–69].

3.2. Interaction

A contract net protocol is used to allow communication between the alliance and its members [9]. Since not all members of the alliance can simultaneously communicate with the opponent, it is assumed that a trusted mediator (or an alliance agent) broadcasts opponent decisions to all members and transmits the alliance decisions to the opponent. It can also be possible to have team negotiation, where some or all members of an alliance negotiate against an opponent, a multi-party negotiation, with an appropriate team strategy. A mediator will represent the alliance while negotiating with an opponent. To allow communication between the opponent and the alliance mediator, an alternating offer bilateral protocol is followed [66]. This trusted mediator may have extra tasks according to the alliance strategy employed. Nevertheless, the complete preferences of the agents are not revealed to this mediator. Every member has its single negotiated model and the mediator adopts the chosen alliance strategy procedure, making decisions by taking into account the concept of that strategy. The interaction protocol used in this model is restricted to communication related to the protocol initiation, the negotiation, and the decision on proposals [70]. There is no interaction between members apart from this, so, they cannot be influenced or influence the others in this model (i.e., there is no persuasion between members).

There are different types of interactions inside an alliance, in the case of a dependent aggregation, the communication will be very limited because the negotiation agent (mediator) will perform the whole negotiation with the opponent(s) and just after signing the contract will inform all the other members about the deal. In the case of an independent aggregation, the communication is responsive, i.e., the members can only respond to the mediator requests but they can inform the mediator in the case of leaving the alliance [71]. A limited negotiation occurs when the members can only interact with the mediator; there is no interaction between them, which is the case for the sector, locally and complex types of alliance formation.

The communication between members is not fully studied in this article because that would suppose that the agents can persuade each other to have their proposals accepted, and this type of complexity is not the focus of this article. However, this complexity can be studied in political sciences, considering the interaction between members of different political parties inside a government alliance. Such as, for example, the application of the Shapley-Shubik index in the decision-making process of team negotiation strategies [72,73]. This index evaluates the strength of agents to persuade or influence others to accept their proposals, inside the decision-making process of an alliance. Other methods for determining the power of an agent inside an alliance have been proposed by [74,75]. Some of the members (dependent customer agents) only receive the information of acceptance or rejection of a proposal. Others, as independent customer agents, cannot send any proposal, but can vote for the acceptance of a proposal that the trusted mediator proposes. The negotiation agents could interact in the whole process if the alliance strategy chosen by them, requests them to do so.

All members, except the dependent customer agents, can leave the alliance before signing a contract with the opponent agent. Dependent agents belong to other members of the alliance, so, they only can leave the alliance if their owners also do so. The next two phases of the process of signing a new bilateral contract are inter-related; the type of negotiation and also the decision process depends essentially on the type of alliance formation, and on the coalition strategy chosen by its members.

3.3. Negotiation and Agreement

In the actual negotiation process, there is an exchange of offers and counter-offers between the alliance and an opponent. If the alliance mediator requests a proposal suggested by its members, they will calculate the proposal taking into account their concession tactics. During the negotiation process, the decision process also takes place, when the mediator receives a proposal from the opponent. All or some of the members can be requested to vote for the acceptance or rejection of the proposal. Also, the proposals sent to the opponent could be proposed and/or voted by all or some of the members depending on the alliance strategy [69–71].

Considering the negotiation between an opponent and the alliance, respectively, when the alliance mediator receives or sends a proposal it can request a voting process to decide the acceptance of a received proposal or its rejection, sending it to its members, it selects the alliance's most voted proposal. In this stage the decision making of the requested agents is equal to the one defined in the "Least-acceptable Agreement, Acceptable Agreements" definition described in [61], they vote yes (1) or no (0) taking into account the comparison between their computed utilities.

The behaviour of the negotiation and decision processes is heavily dependent on the alliance strategy. An alliance strategy defines which decisions have to be taken by a negotiation team, how those decisions are taken, and when those decisions are taken. In a bilateral negotiation process between an alliance and an opponent, the decisions must be taken between the alliance members, which offers are sent to the opponent, and whether opponent offers are accepted or not. Given the fact that a negotiation alliance is formed by more than a single agent, decisions should take into account the interests of the alliance members [67–70].

How decisions are taken will determine the satisfaction level of the alliance with the final decision [70,71,76–78]. Decisions can be taken using a representative, majority rules, unanimity rules, or distinction power. Since all alliance members seek a common goal, and this should not be their first interaction, a certain degree of cooperation and truthfulness among members is assumed [79,80]. Even though a scenario where most of the members lie and play strategically is possible, this possibility has been considered unlikely in this type of practical situation, since they are cooperative in nature, and modelling this type of scenario is complex [81,82]. Typical alliances can be selected to cover the spectrum of participation in alliance decisions such as: the less participative in decision making (representative); strategies that involve a majority of members (similarity simple voting); strategies that carry out unanimous decisions (similarity-based unanimity board voting); and strategies that take into account every member's weight in the alliance (similarity distinction voting) [55,57].

3.4. The Adaptation of the Negotiation Model to CECs

CECs that only have consumers and prosumers as agents should select one of their members as the representative mediator to negotiate with opponents on behalf of the entire alliance. All members have information about their own tariff and net load, computing the score of each proposal based on their utility function. Every member should indicate to the mediator the energy they need to buy or sell per every market period. Some members can also have negotiation strategies, computing their prices and proposing them to the mediator. The mediator should send a request to vote on all opponent proposals, its proposal, and all member proposals. All members should vote for the best proposal that is selected according to the defined team strategy. If one of the opponent proposals is the most voted proposal, the negotiation ends with an agreement, otherwise, the mediator sends to opponents a counter-proposal with the most voted proposal. The negotiation continues until one proposal is accepted or all parties withdraw from the negotiation. If the CEC is also composed of producers, aggregators, and other players, the mediator should be carefully selected according to the main goal of the CEC. These players also have their own goals and utility functions that may differ between them. Accordingly, the achievement of agreements in an alliance composed of players with different goals may be more difficult and lead to outputs that could not be satisfactory to all evolved parties. Generally, CECs are composed of local small players that do not have enough expertize to negotiate in EMs. So, the most experienced between them or even an external negotiator should be selected as the trusted mediator. CECs can have an enormous number of members from different types, so, while managing their resources can be done with some effort using a contract net protocol, the number of messages exchanged while negotiating a tariff can be very high to manage [9].

The RM-IDM strategy reserves to the trusted mediator the computation of tariffs, but allows that all members vote on the acceptation of a tariff, between the mediator's tariff and the tariffs proposed by opponents. Using this strategy, it is possible to vote for the best tariff between a limited number of proposals. The RE strategy lets the mediator selects the tariff, which can result in very diverse utilities and withdrawal members. The SSV strategy is a bad choice in case of alliances with a relatively high number of members. Using this strategy, all members can propose a tariff and vote on the acceptance of the best tariff. The most voted tariff is accepted between a (potential) enormous number of tariffs, which means that a tariff with few votes can be accepted, if the majority of the members vote for the acceptance of their own tariff, which can decrease the members' utility. To deal with this limitation, a SBV strategy can be used, where all agents score proposals from the best to the worst, giving them a different number of votes, accordingly. Each member gives to its best proposal a number of votes equal to the number of proposals, and to the worst proposal only one vote. The proposal with more votes is selected. The literature indicates that this strategy is the one that can lead to higher utilities for the members of the alliance, but it is computationally very heavy [55]. Per each negotiation step, each member will send to the trusted mediator their own proposal, and will receive all proposals, rank all proposals and receive the final result. So, the number of messages per proposal is proportional to the number of members raised to the 4th power. In the FUM strategy, all members have to accept the same proposal. All members can suggest a tariff, and until they vote for the acceptance of the same tariff, there is an extensive exchange of messages, which increases the computational complexity of the negotiation. In alliances with a substantial number of negotiating agents, when using a FUM strategy is very hard to achieve an agreement [55].

Against this background, as CECs are composed of a relevant number of unexperienced market participants, the most reasonable team strategy that they can use is the RM-IDM [23]. The SSV will (potentially) result in a bad agreement to the majority of members, and the other strategies are computationally heavy. The next section presents a case study considering the negotiation of a PPA between CECs, using the RM-IDM strategy, and RES.

4. Case Study on the Negotiation of a PPA between CECs and RES

This study concerns the negotiation of a power purchase agreement (PPA) between a CEC and an aggregator, that manages all wind farms in Portugal, for the period 2012–2013. This study considers real data of 312 consumers and 227 wind farms from Portugal during 2011–2013 (see the Data Availability Statement). By signing a PPA with the wind aggregator, the CEC is responsible for all deviations from the wind farms and the wind aggregator receives a liquid value from the agreement, the negotiated price.

4.1. Data

Real data from 2011 is used to forecast prices and consumption during the period 2012–2013. The consumers represent around 5% of the Portuguese demand, while the wind farms with an installed capacity of 4730 MW, represent all Portuguese wind farms. This study will evaluate the benefit of consumers by forming an alliance as a CEC, and negotiating PPAs with RES.

In Portugal, during 2013 the regulated tariff of consumers considered a value of 140.50 €/MWh for electricity, the energy part being 70.60 €/MWh, the grid-access

65.90 €/MWh and the commercialization tax equal to 2.5 €/MWh [15]. Currently, by forming an alliance as a CEC with self-consumption, consumers have a discount of 50% in the grid access cost. Furthermore, if the CEC participates directly in the market without an intermediary, as a retailer, it also has a discount on the commercialization tax.

The CEC has an average consumption of 212 MWh and the wind farms capacity factors in Portugal stand around 25%. So, to be carbon-neutral, the CEC should negotiate a PPA of around 848 MW with wind farms. All environmental, operational, and economical metrics used in this case study can be found in [12].

In 2011 the wind farm remuneration from EMs was 36.05 €/MWh and was expected to decrease by 2012 and 2013 to 35.87 €/MWh and 32.90 €/MWh, respectively. The aggregator considered 36.00 €/MWh as the minimum price for accepting a deal but had the goal of achieving a value until 60 €/MWh, its initial proposal.

4.2. Negotiation and Results

Consumers that did not form an alliance into a CEC were restricted to a regulated or retail tariff. The regulated tariff was indicated by the regulator, while retail tariffs were proposed by competitive retailers. If consumers formed an alliance into a coalition they may have had enough weight to participate in EMs, paying the wholesale market price of electricity plus taxes.

The CEC used a representative mediator with individual decision making (RM-IDM) strategy, which means that the representative mediator was the only one that computed and suggested proposals to the alliance, but all members had to vote for their acceptance [24]. The CEC considered a maximum value for this PPA of 65 €/MWh, but had the goal of obtaining a value until 40 €/MWh, its initial proposal.

At the start, both agents used a reasonable strategy, conceding moderately, considering a concession factor of 10% (see [21] for a review about negotiation strategies and tactics). All members of the CEC scored proposals according to a cost function. So, they voted positively for the proposal that minimized their cost. The aggregator scored proposals according to their expected remuneration function, accepting the proposal that maximized their remuneration.

The negotiation started with the RM indicating the CEC needs for a PPA of 848 MW and requesting the electricity price of the energy-part of the variable-term. The aggregator started by indicating that for that amount of power the energy price was 60 €/MWh. The RM computed a price equal to 40 €/MWh and sent both proposals to all members that were to vote on the acceptance of the RM's proposal. The negotiation continued until the CEC accepted the sixth proposal of the aggregator for 50.17 €/MWh, the PPA price.

Table 1 presents the main results of the case study from the point of view of the consumers and the wind aggregator. It presents the total costs of the consumers with the variable term of the electricity, considering that they: (i) have a retail tariff, (ii) form a CEC and negotiate in EMs, and (iii) form a CEC, negotiate in EMs and sign a PPA with wind farms. Furthermore, it also presents the remuneration of the wind aggregator, considering its participation in EMs, or the signature of the PPA with the CEC.

Table 1. Average consumer costs before taxes (VAT) considering the variable tariff, and the wind aggregator remuneration from an individual and community (CEC) perspective.

Player	Details	Energy-Part (€/MWh)	Other-Part (€/MWh)	Total Cost (€/MWh)	Technology Remuneration (€/MWh)
Consumer	Regulated tariff	70.60	69.90	140.50	-
CEC (Consumers)	Market-based	48.11	67.40	125.51	-
CEC (Consumers)	PPA	55.56	38.45	95.01	-
Wind Aggregator	Market-based	-	-	-	43.28
Wind Aggregator	PPA	-	-	-	50.17

Analysing Table 1, it is possible to verify that consumers are paying more 47% for the energy-part of the regulated tariff (70.60 €/MWh) when compared to the wholesale price of energy (48.11 €/MWh), even considering penalties with real-time deviations. Retail tariffs have final prices similar to regulated tariffs, which means that retailers have a markup of around 12% if considering the whole variable term of the tariff. If the CEC signs a PPA with the wind aggregator for 50.17 €/MWh, it may increase its costs with the energy part of the variable term of the electricity by 15%, when compared to only bidding at EMs, mainly because the CEC is responsible for the deviations of the wind aggregator. However, by using wind power production for self-consumption, the CEC has a discount of 50% in the grid access tax. So, the total costs of its members for electricity were reduced by 33% compared with regulated tariffs, and by 24% compared with EMs bidding. Furthermore, by signing a PPA with a wind aggregator, the CEC is carbon-neutral to electricity consumption, i.e., consumes less electricity than the acquired value in the PPA. Also, it has an energy sustainability index of 0.65, which means it consumes exactly 65% of wind power production. The remaining energy, the CEC buys or sells in EMs in case of real-time energy scarcity or excess, respectively. This happens because wind power production is not completely correlated with the CEC demand.

After the end of the government incentives, the wind farm remuneration is not guaranteed. So, they have to participate in the market, facing price volatility and leading with their production uncertainty, paying substantial penalties because of their real-time imbalances to market commitments. The same is true for new wind farm projects that could have difficulties in being financed because of the uncertainty related to their remuneration. Against this background, the negotiation of long-term PPAs may give the stability that new wind farms projects need to be financed, and at the same time increase their remuneration. The alliance of wind farms with flexible consumer and/or storage solutions can mitigate their unbalance quantities [83].

Analysing Table 1, it is possible to verify that by signing a PPA, the wind aggregator increases its remuneration by 16%, receiving a fixed price such as in feed-in-tariffs, and passing its responsibility with imbalances to the buyer. Against this background, the negotiation of PPAs between demand-side players and VRES can lead to mutual benefit agreements. Demand-side players can become carbon-neutral and obtain green certificates from VRES production, and at the same time complement VRES deviation with their own, mitigating part of it. VRES can receive stable remuneration that enables their financing. Furthermore, by not being responsible for deviations, VRES may obtain a higher remuneration.

5. Conclusions

The new European Union (EU) legislation, with ambitious decarbonisation goals of future power systems towards near 100% renewable penetration, activated significant governmental incentives for new investments in renewable energy sources (RES), such as wind, solar PV, and biomass. These incentives consist of feed-in tariffs with values significantly higher than wholesale market prices of electricity, which contribute to the tariff deficit, paid by consumers. The increase in the production of PV panels leads to a substantial reduction in their production costs (scale economy), and has resulted in several investments in this technology without the need of government incentives. However, this technology has a stochastic profile, which means that it has an uncertain production that reduces its uncertainty the closer to real-time operation.

Day-ahead markets of electricity are the most liquid physical markets, but they close on the day-ahead of real-time operation, several hours before unit commitment. Against this background, both variable RES and demand-side players have to rely on power forecasts while bidding at day-ahead markets. These players can try to update their power bids to more trustable values, closer to real-time operation, on intraday and real-time markets of electricity, based on more reliable power forecasts. Unfortunately, these power forecasts also have errors which, during real-time operation, lead to imbalances between demand and supply of electricity. These imbalances have to be fixed in the ancillary services, paid by the imbalance parties, resulting in penalties to these players. The increase in the VRES production normally increases the need to balance the system, increasing the costs of ancillary services. High shares of VRES in power systems will lead to the need for flexibility in order to avoid curtailments of VRES in case of energy excesses, and extremely high peak prices or even the loss load expectation in case of energy scarcity. The alliance of distributed generation, consumption, and storage solutions (potentially) can be very important to provide the flexibility required for future power systems with near 100% RES penetration, which should be subject to security experiments.

This article focused on the alliance agent and its functions in liberalized electricity markets. It presented a model for single agents that has been adapted to an alliance agent model. This article adapted this model to Citizen Energy Communities (CECs), describing the main phases of the model. This model consists of several intra-team strategies, some of them used in several cases and sectors in the world, and of the negotiation and decision structure of the alliance model in electricity markets. Furthermore, this article presents how the model of alliance agents can be adapted to CECs, considering their formation, and how their members interact and decide between them and negotiate mutually beneficial agreements with opponents. It also presents a case study that tests the model by considering the negotiation of a power purchase agreement (PPA) between the CEC and a wind aggregator. This bilateral agreement leads to a mutual benefit for both parties. The CEC reduces its member costs for electricity by 33%, and becomes carbon-neutral in relation to electricity consumption. The wind aggregator increases its remuneration by 16%, and passes the responsibility for imbalances to the CEC.

Decarbonisation of all sectors of activity leads to a need for energy flexibility and electrification, on which demand-side agents will have an important role. For future carbon-neutral societies, active participation of the demand-side in energy markets is crucial to economically efficient societies, which can be done through CECs. CECs may comply with the goal of economically efficient carbon-neutral societies. Studying and testing the formation, interaction, and negotiation among alliances of the electricity sector seems appropriate to increase the participation and flexibility of small players of the distribution grid in the power system. Furthermore, the active participation of demand-side players in flexibility markets or demand response programs may accommodate higher quantities of distributed generation and incentivise new VRES capacity.

How different team strategies can improve CEC outputs and how demand response can enable their participation in the ancillary services will be studied in future work.

Funding: This work received funding from the EU Horizon 2020 research and innovation program under project TradeRES (grant agreement No 864276).

Data Availability Statement: The consumption dataset of the consumers can be found at https://archive.ics.uci.edu/ml/datasets/ElectricityLoadDiagrams20112014# (accessed on 22 September 2021). The features of the wind farms are available at http://e2p.inegi.up.pt/?Lang=EN (accessed on 22 September 2021). The market results of the Iberian market of electricity can be found at https://www.mercado.ren.pt/EN/Electr/MarketInfo/MarketResults/Pages/default.aspx (accessed on 22 September 2021). The wind farms and consumption forecasts are available at https://www.mercado.ren.pt/EN/Electr/MarketInfo/Load/TotalLoad/Pages/default.aspx (accessed on 22 September 2021). The observed wind farms productions and their performance indexes, such as the total demand can be found at https://www.centrodeinformacao.ren.pt/EN/InformacaoExploracao/Pages/EstatisticaMensal.aspx (accessed on 22 September 2021).

Conflicts of Interest: The author declares no conflict of interest.

Abbreviations

AMES	Agent-based Modelling of Electricity Systems
BESS	Battery energy storage system
CEC	Citizen energy community
DCF	Dynamic coalition formation
DCF-S	DCF based on simulation
DG	Distributed generation
EM	Electricity market
EMCAS	Electricity Market Complex Adaptive System
EV	Electric vehicle
EU	European Union
FUM	Full unanimity mediated
GAPEX	Genoa Artificial Power Exchange
GenCo	Generation Company
ISO	Independent System Operator
MAS	Multi-agent System
MASCEM	Multi-Agent Simulator of Competitive Electricity Markets
MATREM	for Multi-Agent Trading in Electricity Markets
PPA	Power purchase agreement
PV	Photovoltaic
RE	Representative
RES	Renewable energy sources
RM	Representative Mediator
RM-IDM	Representative Mediator with Individual Decision Making
SEPIA	Simulator for Electric Power Industry Agents
SREMS	Short Medium run Electricity Market Simulator
SBV	Similarity Borda Voting
SSV	Similarity Simple Voting
VAT	Value Added Tax
VPP	Virtual power player
VRES	Variable renewable energy sources
WPP	Wind power producer

References

1. Kirschen, D.; Strbac, G. *Fundamentals of Power System Economics*, 2nd ed.; John Wiley & Sons: Chichester, UK, 2018.
2. Algarvio, H.; Lopes, F.; Sousa, J.; Lagarto, J. Multi-agent electricity markets: Retailer portfolio optimization using Markowitz theory. *Electr. Power Syst. Res.* **2017**, *148*, 282–294. [CrossRef]
3. Algarvio, H.; Lopes, F. Agent-based Retail Competition and Portfolio Optimization in Liberalized Electricity Markets: A Study Involving Real-World Consumers. *Int. J. Electr. Power Energy Syst.* **2021**, 107687. [CrossRef]
4. Lopes, F.; Coelho, H. Overview of wholesale electricity markets. In *Electricity Markets with Increasing Levels of Renewable Generation: Structure, Operation, Agent-Based Simulation and Emerging Designs*; Springer: Cham, Switzerland, 2018. [CrossRef]
5. Algarvio, H.; Couto, A.; Lopes, F.; Santana, S.; Estanqueiro, A. Effects of Regulating the European Internal Market on the integration of Variable Renewable Energy. *WIREs Energy Environ.* **2019**, *8*, 346. [CrossRef]
6. Strbac, G.; Papadaskalopoulos, D.; Chrysanthopoulos, N.; Estanqueiro, A.; Algarvio, H.; Lopes, F.; de Vries, L.; Morales-España, G.; Sijm, J.; Hernandez-Serna, R.; et al. Decarbonization of Electricity Systems in Europe: Market Design Challenges. *IEEE Power Energy Mag.* **2021**, *19*, 53–63. [CrossRef]
7. Shahidehpour, M.; Yamin, H.; Li, Z. *Market Operations in Electric Power Systems: Forecasting, Scheduling, and Risk Management*, 1st ed.; John Wiley & Sons: Chichester, UK, 2003.
8. Lopes, F. Electricity Markets and Intelligent Agents. Part II: Market Architecture and Structure. In *Electricity Markets with Increasing Levels of Renewable Generation: Structure, Operation, Agent-Based Simulation and Emerging Designs*; Series: Studies in Systems, Decision and Control; Springer: Cham, Switzerland, 2018; Volume 144, pp. 23–48.
9. Smith, R.G. The contract net protocol: High-level communication and control in a distributed problem solver. *IEEE Trans. Comput.* **1980**, *29*, 1104–1113. [CrossRef]
10. Meeus, L.; Purchalaa, K.; Belmans, R. Development of the Internal Electricity Market in Europe. *Electr. J.* **2015**, *18*, 25–35. [CrossRef]
11. Sandholm, T.; Lesser, V. Coalitions among computationally bounded agents. *Artif. Intell.* **1997**, *94*, 94–137. [CrossRef]

12. Algarvio, H. The Role of Local Citizen Energy Communities in the Road to Carbon-Neutral Power Systems: Outcomes from a Case Study in Portugal. *Smart Cities* **2021**, *4*, 840–863. [CrossRef]
13. European Commission. Communication from the Commission to the European Parliament, the Council, the European Economic and Social Committee, the Committee of the Regions and the European Investment Bank: Clean Energy for All Europeans (COM/2016/0860 Final). Available online: https://eur-lex.europa.eu/legal-content/EN/TXT/?uri=CELEX%3A52016DC0860 (accessed on 29 October 2021).
14. European Commission. Regulation (EU) 2019/943 of the European Parliament and of the Council on the Internal Market for Electricity. 5 June 2019. Available online: http://data.europa.eu/eli/reg/2019/943/oj (accessed on 29 October 2021).
15. ERSE. Tariffs and Prices-Electricity. Available online: https://www.erse.pt/en/activities/market-regulation/tariffs-and-prices-electricity/ (accessed on 18 March 2021).
16. Algarvio, H.; Lopes, F.; Couto, A.; Estanqueiro, A. Participation of Wind Power Producers in Day-ahead and Balancing Markets: An Overview and a Simulation-based Study. *WIREs Energy Environ.* **2019**, *8*, e343. [CrossRef]
17. Algarvio, H.; Lopes, F.; Couto, A.; Estanqueiro, A.; Santana, J. Variable Renewable Energy and Market Design: New Market Products and a Real-world Study. *Energies* **2019**, *12*, 4576. [CrossRef]
18. Bellifemine, F.; Caire, G.; Greenwood, D. *Developing Multi-Agent Systems with JADE*; John Wiley & Sons: Chichester, UK, 2007.
19. Algarvio, H.; Lopes, F. Risk Management and Bilateral Contracts in Multi-agent Electricity Markets. In *Highlights of Practical Applications of Heterogeneous Multi-Agent Systems, Proceedings of the PAAMS 2014 International Workshops, Salamanca, Spain, 4–6 June 2014*; Springer: Berlin/Heidelberg, Germany, 2014; pp. 297–308.
20. Algarvio, H.; Lopes, F.; Coelho, H. Bilateral Contracting in Multi-agent Electricity Markets: Negotiation Strategies and a Case Study. In Proceedings of the International Conference on the European Energy Market (EEM-13), Stockholm, Sweden, 27–31 May 2013; IEEE Computer Society Press: Washington, DC, USA, 2013; pp. 1–8.
21. Algarvio, H.; Lopes, F.; Coelho, H. Negotiating Hour-Wise Tariffs in Multi-Agent Electricity Markets. In Proceedings of the International Conference on Industrial Applications of Holonic and Multi Agent Systems (HoloMAS-13), Prague, Czech Republic, 26–28 August 2013; Springer: Berlin/Heidelberg, Germany, 2013; pp. 246–256.
22. Algarvio, H.; Lopes, F.; Santana, J. Multi-agent Retail Energy Markets: Bilateral Contracting and Coalitions of End-use Customers. In Proceedings of the International Conference on the European Energy Market (EEM-15), Lisbon, Portugal, 19–22 May 2015; IEEE Computer Society Press: Washington, DC, USA, 2015; pp. 1–8.
23. Algarvio, H.; Lopes, F.; Santana, J. Multi-agent Retail Energy Markets: Contract Negotiation, Customer Coalitions and a Real-World Case Study. In *Advances in Practical Applications of Scalable Multi-Agent Systems, Proceedings of the PAAMS Collection: 14th International Conference, Sevilla, Spain, 1–3 June 2016*; Springer: Berlin/Heidelberg, Germany, 2016; pp. 13–23.
24. Algarvio, H.; Lopes, F.; Santana, J. Coalitions of End-Use Customers in Retail Electricity Markets: A Real-World Case Study Involving Five Schools for Children. In Proceedings of the International Conference on Practical Applications of Agents and Multi-Agent Systems, Toledo, Spain, 20–22 June 2018; Springer: Berlin/Heidelberg, Germany, 2018; pp. 312–320.
25. Hunt, S.; Shuttleworth, G. *Competition and Choice in Electricity*; Wiley: Chichester, UK, 1996.
26. Li, H.; Tesfatsion, L. Development of Open Source Software for Power Market Research: The AMES Test Bed. *J. Energy Mark.* **2009**, *2*, 111–128. [CrossRef]
27. Koritarov, V. Real-World Market Representation with Agents: Modeling the Electricity Market as a Complex Adaptive System with an Agent-Based Approach. *IEEE Power Energy Mag.* **2004**, *2*, 39–46. [CrossRef]
28. Cincotti, S.; Gallo, G. Genoa Artificial Power-Exchange. In Proceedings of the International Conference on Agents and Artificial Intelligence, Barcelona, Spain, 15–18 February 2013; pp. 348–363.
29. Praça, I.; Ramos, C.; Vale, Z.; Cordeiro, M. MASCEM: A Multi-Agent System that Simulates Competitive Electricity Markets. *IEEE Intell. Syst.* **2003**, *18*, 54–60. [CrossRef]
30. Oliveira, P.; Pinto, T.; Morais, H.; Vale, Z.; Praça, I. MASCEM An Electricity Market Simulator providing Coalition Support for Virtual Power Players. In Proceedings of the 15th International Conference on Intelligent System Applications to Power Systems, Curitiba, Brazil, 8–12 November 2009.
31. Harp, S.; Brignone, S.; Wollenberg, B.; Samad, T. Sepia: A Simulator for Electric Power Industry Agents. *IEEE Control. Syst. Mag.* **2000**, *20*, 53–69.
32. Lopes, F. MATREM: An Agent-based Simulation Tool for Electricity Market. In *Electricity Markets with Increasing Levels of Renewable Generation: Structure, Operation, Agent-Based Simulation and Emerging Designs*; Series: Studies in Systems, Decision and Control; Springer: Cham, Switzerland, 2018; Volume 144, pp. 189–225.
33. Zimmermann, R.; Thomas, R. PowerWeb: A tool for evaluating economic and reliability impacts of electric power market designs. In Proceedings of the IEEE PES Power Systems Conference and Exposition, New York, NY, USA, 10–13 October 2004; Volume 3, pp. 1562–1567.
34. Migliavacca, G. SREMS-electricity market simulator based Game Theory and incorporating network constraints. In Proceedings of the IEEE Power Tech, Lausanne, Swiss, 1–5 July 2007.
35. North, M.; Collier, N.; Vos, J. Experiences creating three implementations of the repast agent modeling toolkit. *ACM Trans. Modeling Comput. Simul.* **2006**, *16*, 1–25. [CrossRef]

36. Lopes, F.; Coelho, H. Electricity Markets and Intelligent Agents. Part I: Agent Architectures and Capabilities. In *Electricity Markets with Increasing Levels of Renewable Generation: Structure, Operation, Agent-Based Simulation and Emerging Designs*; Series: Studies in Systems, Decision and Control; Springer: Cham, Switzerland, 2018; Volume 144, pp. 49–77.
37. Lopes, F.; Algarvio, H.; Santana, J. Agent-based simulation of electricity markets: Risk management and contracts for difference. In *Agent-Based Modeling of Sustainable Behaviors*; Springer: Cham, Switzerland, 2017; pp. 207–225.
38. Klusch, K.; Gerber, A. Dynamic Coalition Formation among Rational Agents. *IEEE Intell. Syst.* **2002**, *17*, 42–47. [CrossRef]
39. Shoham, Y.; Leyton-Brown, K. Multiagent Systems: Algorithmic. In *Game-Theoretic, and Logical Foundations*; Cambridge University Press: Cambridge, UK, 2008.
40. Peter, A. Microgrids, Virtual Power Plants and Our Distributed Energy Future. *Electr. J.* **2010**, *23*, 72–82.
41. Ausubel, L.; Cramton, P. Virtual power plant auctions. *Util. Policy* **2010**, *18*, 201–208. [CrossRef]
42. Pinto, T.; Morais, H.; Oliveira, P.; Vale, Z.; Praça, I.; Ramos, C. A new approach for multi-agent coalition formation and management in the scope of electricity markets. *Energy* **2011**, *36*, 5004–5015. [CrossRef]
43. Rodrigues, L.; Estanqueiro, A. Integration of renewable sources in the electric system using Virtual Renewable Power Plants. In Proceedings of the 11th International Conference on Electrical Power Quality and Utilisation (EPQU), Lisbon, Portugal, 17–19 October 2011.
44. Baeyens, E.; Bitar, E.Y.; Khargonekar, P.P.; Poolla, K. Wind Energy Aggregation: A Coalitional Game Approach. In Proceedings of the 50th IEEE Conference on Decision and Control and European Control Conference, Orlando, FL, USA, 12–15 December 2011.
45. Goldfarb, L.; Stevenson, D. Aggregation: An Anti-Aggravation Pill for New-Millennium Consumers. *Electr. J.* **1999**, *12*, 78–86. [CrossRef]
46. Halvorsen, B.; Larsen, B. How serious is the aggregation problem? An empirical illustration. *Appl. Econ.* **2013**, *45*, 3786–3794. [CrossRef]
47. Adom, P.K.; Bekoe, W.; Akoena, S.K.K. Modelling aggregate domestic electricity demand in Ghana: An autoregressive distributed lag bounds cointegration approach. *Energy Policy* **2012**, *42*, 530–537. [CrossRef]
48. Corcoran, B.A.; Jenkins, N.; Jacobson, M.Z. Effects of aggregating electric load in the United States. *Energy Policy* **2012**, *46*, 399–416. [CrossRef]
49. Denton, F.; Mountain, D. Exploring the effects of aggregation error in the estimation of consumer demand elasticities. *Econ. Model.* **2011**, *28*, 1747–1755. [CrossRef]
50. Agnetis, A.; Dellino, G.; De Pascale, G.; Innocenti, G.; Pranzo, M.; Vicino, A. Optimization models for consumer flexibility aggregation in smart grids: The ADDRESS approach. In Proceedings of the IEEE First International Workshop on Smart Grid Modeling and Simulation, Brussels, Belgium, 17 October 2011.
51. Ribeiro, C.; Pinto, T.; Morais, H.; Vale, Z.; Santos, G. Intelligent Remuneration and Tariffs for Virtual Power Players. In Proceedings of the 2013 IEEE Grenoble Conference, Grenoble, France, 16–20 June 2013; pp. 1–6.
52. Ha¨ma¨la¨inen, R.; Ma¨ntysaari, J.; Ruusunen, J.; Pineau, P. Cooperative consumers in a deregulated electricity market dynamic consumption strategies and price coordination. *Energy* **2000**, *25*, 857–875. [CrossRef]
53. Hatami, S.; Pedram, M. Minimizing the Electricity Bill of Cooperative Users under a Quasi-Dynamic Pricing Model. In Proceedings of the First IEEE International Conference on Smart Grid Communications, Gaithersburg, MD, USA, 4–6 October 2010.
54. Algarvio, H. Least-Cost Non-RES Thermal Power Plants Mix in Power Systems with Majority Penetrations of Renewable Energy. *Electricity* **2021**, *2*, 403–422. [CrossRef]
55. Sanchez-Anguix, V.; Julia´n, V.; Botti, V.; Garc´ıa-Fornes, A. Studying the impact of negotiation environments on negotiation teams performance. *Inf. Sci.* **2013**, *219*, 17–40. [CrossRef]
56. Ephrati, E.; Rosenschein, J. Deriving consensus in multiagent systems. *Artif. Intell.* **1996**, *87*, 21–74. [CrossRef]
57. Sanchez-Anguix, V.; Julia´n, V.; Botti, V.; Garc´ıa-Fornes, A. Reaching Unanimous Agreements Within Agent-Based Negotiation Teams with Linear and Monotonic Utility Functions. *IEEE Trans. Syst. Man Cybern. Part B* **2012**, *42*, 778–792. [CrossRef]
58. Sanchez-Anguix, V.; Valero, S.; Julia´n, V.; Botti, V.; Garc´ıa-Fornes, A. Evolutionary-aided negotiation model for bilateral bargaining in Ambient Intelligence domains with complex utility functions. *Inf. Sci.* **2013**, *222*, 25–46. [CrossRef]
59. Sanchez-Anguix, V.; Aydogan, R.; Baarslag, T.; Jonker, C. Bottom-up approaches to achieve Pareto optimal agreements in group decision making. *Knowl. Inf. Syst.* **2019**, *61*, 1019–1046. [CrossRef]
60. Clarke, E.H. Multipart pricing of public goods. *Public Choice* **1971**, *11*, 17–33. [CrossRef]
61. Pechoucek, M.; Marik, V. Industrial Deployment of Multi-agent Technologies: Review and Selected Case Studies. *Auton. Agents Multi-Agent Syst.* **2008**, *17*, 397–431. [CrossRef]
62. Wooldridge, M. *An Introduction to Multiagent Systems*; Wiley: Chichester, UK, 2009.
63. Bichler, M.; Kersten, G.; Strecker, S. Towards a Structured Design of Electronic Negotiations. *Group Decis. Negot.* **2003**, *12*, 311–335. [CrossRef]
64. Lewicki, R.; Barry, B.; Saunders, D. *Negotiation*; McGraw Hill: New York, NY, USA, 2010.
65. Thompson, L. *The Mind and Heart of the Negotiator*; Prentice-Hall: Hoboken, NJ, USA, 2005.
66. Raiffa, H.; Richardson, J.; Metcalfe, D. *Negotiation Analysis*; Harvard University Press: Cambridge, MA, USA, 2002.
67. Pruitt, D.; Kim, S. *Social Conflict: Escalation, Stalemate, and Settlement*; McGraw Hill: New York, NY, USA, 2004.
68. Raiffa, H. *The Art and Science of Negotiation*; Harvard University Press: Cambridge, MA, USA, 1982.
69. Lax, D.; Sebenius, J. *The Manager as Negotiator*; Free Press: New York, NY, USA, 1986.

70. Lopes, F.; Mamede, N.; Novais, A.Q.; Coelho, H.A. Negotiation Model for Autonomous Computational Agents: Formal Description and Empirical Evaluation. *J. Intell. Fuzzy Syst.* **2002**, *12*, 195–212.
71. Pruitt, D.; Carnevale, P. *Negotiation in Social Conflict*; Open University Press: Philadelphia, PA, USA, 1993.
72. Shapley, L.S.; Shubik, M. A method for evaluating the distribution of power in a committee system. *Am. Political Sci. Rev.* **1954**, *48*, 787–792. [CrossRef]
73. Banzhaf, J. Weighted voting doesn't work: A mathematical analysis. *Rutgers Law Rev.* **1965**, *19*, 317–343.
74. Brams, S.J.; Lucas, W.F.; Straffin, P.D., Jr. (Eds.) Measuring power in weighted voting systems. In *Political and Related Models*; Springer: New York, NY, USA, 1983; pp. 183–238.
75. Brams, S.J.; Lucas, W.F.; Straffin, P.D., Jr. (Eds.) Power indices in politics. In *Political and Related Models*; Springer: New York, NY, USA, 1983; pp. 256–321.
76. Faratin, P.; Sierra, C.; Jennings, N. Negotiation Decision Functions for Autonomous Agents. *Robot. Auton. Syst.* **1998**, *24*, 59–182. [CrossRef]
77. Osborne, M.; Rubinstein, A. *Bargaining and Markets*; Academic Press: San Diego, CA, USA, 1990.
78. Leech, D. An empirical comparison of the performance of classical power indices. *Political Stud.* **2002**, *50*, 122. [CrossRef]
79. Adelsman, M.; Whinston, A. Sophisticated Voting with Information for Two Voting Functions. *J. Econ. Theory* **1977**, *15*, 145–159. [CrossRef]
80. Saari, G. Mathematical Structure of Voting Paradoxes: II. Positional Voting. *J. Econ. Theory* **2000**, *15*, 55–102.
81. Cormen, T.; Leiserson, C.; Rivest, R.; Stein, C. *Introduction to Algorithms*, 3rd ed.; MIT Press: Cambridge, MA, USA, 2009.
82. Sedgewick, R. *Algorithms in Java, Parts 1–4*, 3rd ed.; Addison-Wesley Professional: Boston, MA, USA, 2002.
83. Algarvio, H.; Lopes, F.; Santana, J. Strategic Operation of Hydroelectric Power Plants in Energy Markets: A Model and a Study on the Hydro-Wind Balance. *Fluids* **2020**, *5*, 209. [CrossRef]