Virtual Associations of Prosumers for Smart Energy Networks Under a Renewable Split Market

Nikolaos D. Doulamis, *Member, IEEE*, Anastasios D. Doulamis, *Member, IEEE*, and Emmanouel Varvarigos

***Abstract*—Feed-in-tariff (FIT) policies are currently employed to internalize the positive externalities of renewable energy sources (RESs). However, FIT is not time varying, failing to model the dynamics of the electricity market. Thus, the concept of the aggregator has been adopted to act as a mediator between the market and RES producers. In this paper, RES aggregation is performed through virtual associations (VAs), which are dynamic clusters of prosumers created through ICT. VAs support the prosumers' active participation in the market, the dynamic formation of the clusters to maximize prosumers' profit and participation, and the fair competition among the VAs and among the prosumers. A VA does not have to be a separate profit-seeking entity, and thus its interests can be perfectly aligned with those of the prosumers comprising it. The fair sharing scheme used favors the most competitive VAs and prosumers, without excluding less competitive ones from the market. Different algorithms to form VAs are examined based on a min–max optimization strategy and fair sharing. Fair sharing provides: 1) incentives to the VAs to increase their competitiveness; 2) increased prosumers' participation; and 3) dynamic interaction with the market. Experimental results obtained on realistic traces reveal the advantages of the proposed market models.**

***Index Terms*—Fair sharing, clustering, market model, renewable energy.**

NOMENCLATURE

Prosumers Properties

$D(r)$:	The requested demand for RES in a region r
SP:	Total RES supply of the prosumers
p_i:	The i-th prosumer
x_i^{max}:	The maximum quantity of energy units that prosumer p_i can offer to the grid
x_i^{cap}:	The maximum energy that prosumer p_i can offer to the grid, while satisfying physical grid constraints.
$\mu_i(r)$:	The cost related to the physical location of p_i and the region r where the energy is demanded
d_i^{cap}:	The desired price requested by prosumer p_i.

The Non-Association (Independent) Case

$\lambda_{MC}^n, \lambda_{MC}$:	The price obtained in the independent case at the n-th iteration of the sharing policy, modelling the Marginal Cost (MC) of the marginal prosumers. λ_{MC} stands for the equilibrium price achieved.
x_i^n:	The energy amount offered by prosumer p_i at the n-th iteration of the algorithm.

The Association Case

$V_i(n), V_i$:	The i-th cluster (VA) created at the n-th iteration of the algorithm. V_i stands for the final i–th cluster created.
λ_{V_i}:	The desired price of cluster V_i, modelling the Average Total Cost (ATC) of its members.
C_{V_i}:	The energy capacity offered by virtual association V_i
D_{V_i}:	The actual energy capacity assigned to virtual association V_i after the fair sharing algorithm
λ_{RES}:	The equilibrium price obtained by the sharing algorithm using the formation of the Virtual Associations.

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N. D. Doulamis and A. D. Doulamis are with the Institute of Communication and Computer Systems, National Technical University of Athens, 157 80 Athens, Greece (e-mail: ndoulam@cs.ntua.gr; adoulam@cs.ntua.gr).

E. Varvarigos is with the Institute of Communication and Computer Systems, National Technical University of Athens, 157 80 Athens, Greece, also with the Computer Technology Institute and Press "Diophantus" Patras, University Campus of Patras, 26504 Rio, Greece, and also with the Department of Electrical and Computer Systems Engineering, Monash University, Melbourne, VIC 3168, Australia.

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I. INTRODUCTION

THE ELECTRICITY produced by Renewable Energy Resources (RES) is qualitatively very different than that produced by other (fossil energy) sources, because of the environmental and other benefits that come with it [1]. The environmental benefits translate into the avoidance of steep CO2 monetary penalties that the rest of the market would have to pay unless a certain percentage of the production comes from RES. Each RES energy unit can therefore be seen as being accompanied by a green credit that benefits the market where it is produced and consumed [2], [3]. If RES energy is sold with today's market structure (at "normal" prices), these green credits would benefit the entire market (especially large producers) and not the actual RES producers that generate them. Thus, green credits constitute a positive externality created by RES producers but primarily benefiting other unrelated

market players. Another positive externality is that RES production is often located close to consumers, which reduces a) transportation losses and b) investments in the distribution network.

The way we propose to internalize the positive externalities so as to benefit RES producers is by introducing a different market model that values directly or indirectly RES externalities. Evaluating directly the value of the externalities would be difficult or impossible. Our (indirect) approach is to promote *a RES market agent as a split market interface* that is integrated into the traditional market. Due to political choices (e.g., EU RES Directives [4]) the traditional electricity market is obliged to trade a certain amount of RES units as part of the energy mix for electricity production. The required RES share is defined as a RES demand from the traditional market to the RES market agent. As a response, the RES market agent will issue a price bid on the traditional market. Because a split framework is assumed, the RES market price is different from the price on the traditional market.

Numerous small *prosumers* are the main sellers of renewable energy. A prosumer is an entity that is simultaneously a producer and a consumer of energy, and possibly also has Demand Response (DR) capabilities that can help shape its net output based on market considerations. In general, there are contradictory interests between the traditional market (i.e., *RES Buyer*) and RES prosumers (i.e., *RES Sellers*). The Buyer tries to purchase RES units at the cheapest possible price, while the Sellers aspire to offer their RES energy at the maximum possible one. Considering that RES sellers act independently and have small individual capacities and very small marginal cost (no fuel is involved), they have to accept a price equal to their marginal cost and well below their average total cost, resulting in unfair pricing for prosumers and an unsustainable RES business. Therefore, different market models need to be investigated for the RES market, which is one of the main topics addressed in the present paper.

A. Previous Works

One pricing model used to internalize RES positive externalities is Feed-In-Tariff (FIT) [5]. FIT is a subsidy policy, where RES generators are credited to sell their energy at higher than normal market prices. With FIT, the RES price is determined independently of the (variable) electricity demand-supply. For this reason, other subsidy market models determine a fixed rate for RES prosumers as a mark-up to the normal market price. Although these policies present environmental benefits, by modeling to some extent the green credits of RES and also reducing energy dependence, the fixed rate *is not time varying, failing to capture the dynamics of the electricity market*. In this context, and to further marketize the time varying value of RES, carbon/green credit markets have been discussed. This results into *a RES market interface acting independently and competitively to the traditional electricity market* [6], a concept that has attracted interest recently. Examples include (i) the U.K. PICLO project, which investigates a peer to peer marketplace for RES [7], (ii) the work of [8] that proposes a split RES market, and (iii) the recent study of U.K. Department of Energy & Climate Change (DECC) [9] that argues for a distributed instead of a centralized marketplace for RES.

Alternative schemes exploit the concept of an aggregator, acting as a mediator between the traditional and the RES suppliers. The work of [10] presents a two-stage market model for power transactions, where an aggregator seeks to optimize its profit. Similarly, in [11] the aggregator starts from a low price and gradually excludes RES entities to maximize its benefit. Optimization of aggregator's profit is also presented in [12]. A game-theoretic framework is adopted in [13] to form coalitions that minimize distribution losses through an optimal matching algorithm. In the same context, the work of [14] establishes a Stackelberg game between providers and end users, where providers behave as leaders maximizing their profit, and end users act as followers maximizing their individual welfare. An uncertainty analysis on both the operator's and users' sides is performed in [15], based on a temporal linear pricing strategy that exploits a non-cooperative or a Stackelberg game [16]. Combination of evolutionary and game-theoretic approaches for multi-objective optimization is presented in [17], while [18] discusses the effect of uncertainties in RES production and real-time pricing.

The main limitations of the aforementioned approaches are that they use business models for the aggregators based on the difference between the price negotiated with the traditional market and the price negotiated with prosumers, trying to maximize aggregator's profit [10]–[12]. In these works, the aggregator is an intermediate profit-seeking entity that tries to purchase RES units at the cheapest possible price, while it aspires to offer them at the maximum possible one, obtaining a profit from the difference. Another limitation is that prosumers are often numerous, of small capacity, and unable to make direct bids to the market, interacting with the aggregator in a passive rather than an active way.

To address these difficulties, methods trying to obtain a better alignment between the welfare of aggregators and that of prosumers have been presented in the literature. Particularly, in [19] a dynamic demand response algorithm is introduced to simultaneously target efficiency and fairness. The mechanism is designed to increase participation by rewarding customers using coupons or an optimal cost operation especially during peak periods. In the same context, [20] encourages customers' participation through a heuristic optimization strategy, implemented in the form of a genetic algorithm. The method optimizes the profit of the aggregator and customers' participation by providing Customer Incentive Pricing (CIP) policy. The key objective of the aforementioned approaches is to dynamically and cooperatively balance the participation of prosumers and the profit of the aggregator. The works of [21], [22] deal with the case of multiple aggregators. More specifically, [21] develops a bi-objective optimization framework, using a cooperative game theoretic approach, to determine the cost allocation among the aggregators, trading off stability versus fairness. The work in [22] combines particle swarm optimization for a data-driven pricing strategy among the utility and multiple aggregators. Optimization methods that account for uncertainties in the demand-response are presented

in [23] and [24] mainly based on risk-constrained stochastic programming.

Other works support an active interaction of prosumers with the aggregator to achieve their optimal benefits. Particularly, in [25] reinforcement learning is investigated to promote such an active interaction in the power market. In [26] prosumers, through their smart meters, choose different data aggregator units based on an evolutionary game. Other approaches examine the interaction between aggregators and consumers through curtailing the flexible loads [27], [28].

B. The Proposed Contribution

In this paper, we introduce an alternative approach of prosumers' participation in the market by allowing the dynamic creation of Virtual Associations (VAs), *i.e., clusters of prosumers,* for RES aggregation. Prosumers in a VA agree to operate together in the market as a single entity.

VAs are smart tools for RES energy aggregators that support active prosumers' interaction and dynamic formation of the clusters, aiming to maximize both prosumers' profit and participation. The latter aim avoids static contractual agreements that could manipulate the market. Our model also promotes a fair competition both among different VAs and among prosumers in a given VA. This fair sharing scheme favors, on the one hand, the most competitive VAs and prosumers against the less competitive ones. On the other hand, it does not punish less competitive VAs and prosumers by excluding them from the market and thus forcing them to perish.

The virtual association concept has been supported by European Union (EU) research activities under the project VIMSEN "Virtual Microgrids for Smart Energy Networks" [19]. The project implements a novel ICT platform and introduces dynamic matching schemes to support the practical deployment of VAs. VIMSEN delivers a *scheduler*, which is Web-based interface, acting as an *ICT mediator* between small-scale prosumers and the electricity market. The VIMSEN scheduler is a software interface with the role of maximizing the number of registered users (prosumers). A VA is *not* a profit-seeking intermediate player, but a software entity that tries to benefit both the small RES producers and the market. Our concept resembles the software platform of cell phones store markets, which act as distributors of apps developed and do not specify the price of an app or the Point Of Sales (POS), thus serving as an interface between the customers and the retailers.

In this paper, VAs are formed using a min-max clustering algorithm. Different sharing policies are discussed to distribute the requested energy demand among the VA clusters, namely: (i) the Winner Takes All, (ii) Equal Volume Sharing, (iii) Equal Income Sharing and (iv) Rank-based Fair Sharing policies. Based on Bertrand Competition Model principles [30], [31], we derive the Nash equilibrium of the prices that the prosumers offer to the market for the four sharing policies investigated. In this context, we show that a fair sharing distribution among the VAs results in a stable market operation, since the most competitive (cheapest) association bestows the highest revenue share in comparison to the less competitive ones. Therefore, fair sharing provides incentives to prosumers to be more competitive at the following biding periods. In contrast, other sharing policies exhibit market power issues.

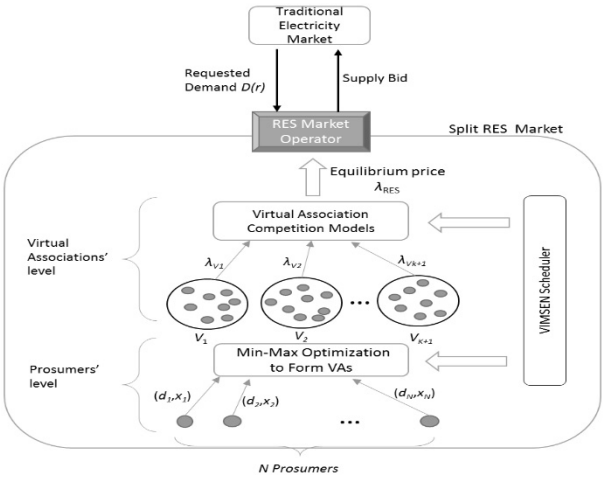

Fig. 1. RES market model as a split agent to the traditional energy market. Such a RES market may exist for a specific region r, to account for regional externalities and constraints.

The remainder of this paper is organized as follows: Section II describes the RES Split Market and the respective VA models. Section III formulates the VA assignment problem, while Section IV presents the min max optimization strategy to form VAs at prosumers' level and Section V discusses the VA competition model. Section VI discusses the competition among VAs based on the Bertrand Model. Finally, Section VII provides experimental results and comparisons with other methods while Section VIII draws the conclusions.

II. Split RES Market Agent

A. Market Description

Fig. 1 presents an overview of the proposed split and competitive RES market. Each market entity, namely the traditional electricity market and the RES market, have their internal optimization methods in order to maximize their own (contradictory) benefits. This results in a highly dynamic and competitive framework avoiding market manipulation by some of the players. In the following, the main steps (the workflow) for the interactions between the traditional and the RES market are presented.

Step #1: Initially, the traditional electricity market requests an amount $D(r)$ of RES units to cover the needs of region r. This amount is derived from the requirement of the traditional market to internalize the positive RES externalities in region r.

Step #2: The RES market agent responds to this demand with an equilibrium price λ_{RES} as well as a group of prosumers that are willing and able to satisfy the requested demand at that price in region r (when confusion cannot arise, we will suppress the dependence on region r). Physical constraints are also considered in determining this ability, in the form of power flow equations that have to be feasibly satisfied with respect to the capacity of the grid.

In order to define the equilibrium price λ_{RES}, algorithms both at the level of the prosumers and at the level of virtual

associations are used, as detailed in subsequent sections. At the prosumers' level, each prosumer p_i declares an amount of x_i RES units he/she is willing to offer at price d_i. Then, a mini-max optimization algorithm is executed to form virtual associations (VAs), that is, clusters of prosumers that agree to operate together in the market as a single entity (see Section V). At the VA level, first the common price λ_{V_i} for each VA is determined to maximize the benefits of its members. In the following, sharing algorithms are activated to select the amount of energy that each VA will contribute to the traditional market. This way, the equilibrium price λ_{RES} is set (see Section VI). The min-max optimization strategy used to form the VAs (prosumers' level) and the models used to determine the equilibrium price λ_{RES} through demand sharing among the VAs (Virtual Associations' level) are implemented by the VIMSEN scheduler (see Section IV.C). Our focus in subsequent sections will be to describe the aforementioned algorithms.

Step #3: The traditional market evaluates the RES market offer in order to check whether it is beneficial or not to accept the offer $D(r)$ at the price λ_{RES}. If this offer is not beneficial, the traditional market prefers to pay emission and other penalties and foregoes the positive green and other externalities.

B. The Virtual Association Models and Market Issues

It is useful to introduce some related definitions and recall some well-known facts from economic theory. The Marginal Cost (MC) of a producer is the change in its total cost when another energy unit is produced (i.e., it is the derivative of the production cost with respect to the output quantity). MC includes only costs that vary with the level of production, and is not related to fixed or initial investment costs. In contrast, the Average Total Cost (ATC) is the total cost divided by the number of units produced [32]. It is equal to the sum of average variable and fixed costs, including amortized initial investment costs, over the output quantity. A particularity of RES is that because of its high investment costs and low operational costs (no fuel), MC is *significantly* smaller than ATC.

Several matching algorithms are investigated in this paper to form the VAs for each of the model cases described next.

Independent Prosumers-The Non-Association Case: The prosumers act independently of each other, without forming VAs. Since prosumers are small and numerous, they are unable to bid up the price. In this case, and assuming a uniform price scheme [see Eq. (11a)], the price that prosumers get paid, according to standard economic theory, is equal to the marginal cost (MC) of the marginal prosumers (i.e., the most expensive ones). Variation in MC among prosumers is rather small, especially when we focus on small RES prosumers of similar production properties. Consequently, even if they operate at the MC of the most expensive prosumers, they will operate close to their own MC, and their benefits will be minimal.

Market Issues: In this case, small-scale prosumers, operating independently without forming VAs, have no ability to bid up the price and they operate close to their MC, or at most equal to the MC of the marginal prosumer.

The Virtual Association Models: In this case, prosumers are clustered together in order to form bigger entities (Virtual Associations-VAs) regarding RES supply. This way, they are able to directly participate in the market providing negotiable price bids. This allows prosumers to sell their energy at their desired price (i.e., close to their ATC), which is much greater than MC for small production units [32]. In the following, we present different algorithms to form VAs under the Virtual Associations Model, and we discuss respective market issues.

1. The *Winner Takes All Policy:* Here, only the most competitive VA, containing the cheapest prosumers, is assigned to deliver the RES demand $D(r)$ at region r. The remaining (more costly) prosumers are excluded from the market.

Market Issues: The Winner Takes All policy reduces market participation, as several prosumers are excluded from it. Smaller participation also raises market power problems, since few players get more power. Usually, small scale prosumers are less competitive and are the ones to eventually perish.

2. *The Equal Volume Sharing Policy:* As an alternative policy to the Winner Takes All, here we allow more than one VAs to participate in the market. In particular, in the Equal Volume Sharing case, all the VA clusters get an equal share of the market, irrespectively of the price (competitiveness) they offer.

Market Issues: Such a matching scheme provides no incentives for prosumers to improve their competiveness, resulting in instabilities in the RES price. The less competitive prosumers receive the same market share, and therefore more income than the more competitive ones.

3. The Equal Income Sharing Policy: An alternative matching scheme is to assign shares to the VAs that are proportional to their competiveness (i.e., inversely proportional to their prices), in which case they all get equal income.

Market Issues: This matching scheme also leads to instabilities since prosumers' profit remains the same regardless of their competitiveness, providing no real incentives for the prosumers to become cheaper at following bids.

4. The Rank-Based Fair Sharing Policy: A more interesting case is to distribute the shares among the VAs so that more competitive prosumers receive more income (and even more profit) than less competitive ones. To implement this scheme, a Rank-based Fair Sharing algorithm is introduced, which considers the competitiveness order of a VA for the market share distribution. Particularly, VAs that are ranked higher in terms of their competiveness, receive greater shares than in the equal income sharing case against the remaining ones.

Market Issue: The Rank-based Fair Sharing policy leads to a competitive framework, avoiding market manipulation issues from VAs. Particularly, in case that some prosumers maliciously "act" to gain extra profit, the Rank-based Fair Sharing algorithm favors more competitive clusters against less competitive ones. This is because the prosumers in higher ranked VAs share among themselves larger incomes than those in lower ranked VAs. This motivates costly prosumers to try to operate more competitively at subsequent time intervals, in order to increase their market share.

***Other Market Issues*:** A feature that prevents market manipulation is the dynamic process used in the formation of

TABLE I
DISCUSSION ON MARKET ISSUES RELATED WITH THE DIFFERENT MODELS TO FORM THE VAs

Policy	Discussion on Market Issues
Independent case	Prosumers are small, lacking the critical size, and operate close to the marginal cost of the marginal prosumer. Assuming similar production features for the prosumers, their benefits are small, since MC<<ATC.
Winner Takes All	Less competitive (usually small-scale) prosumers are excluded from the market and eventually perish. The most competitive prosumers get more power and will finally monopolize the market.
Equal Volume Sharing	All RES prosumers participate, but no incentives are given to the prosumers to improve their competiveness, resulting in instabilities (if a prosumer sets a higher price, he/she receives more income) and market power issues.
Equal Income Sharing	Prosumers tend not to change their price at following biding intervals, since they receive proportional shares in the market. Therefore, the price is set arbitrarily.
Rank-based Fair Sharing	The more competitive prosumers are favored against the less competitive ones and simultaneously all prosumers participate in the market, resulting in market stability and high RES participation and penetration.
Other marker Issues	(a) Contradicting interests are in place between the traditional market and RES prosumers. An unfair price from RES will not be accepted, since the traditional market will decide not to internalize the green credits of RES. (b) No a priori agreements are considered among prosumers. (c) Dynamic clustering avoids market manipulation from maliciously acting prosumers.

VAs. No a priori agreements exist among prosumers, and the clusters are dynamically created according to market demand-supply requirements and the physical constraints. Also, there are competitive and contradictory interests among the traditional market players and RES prosumers. For instance, an unfair price from the RES market agent to the traditional market, due to market manipulation, will not be accepted. In this case, the traditional market will decide to forego the green credits from RES and consume no such energy, forcing RES prosumers to become more competitive at subsequent biding periods.

Virtual associations for smart energy grid target the short-term market. The proposed market model maximizes the benefits of RES prosumers under a competitive framework with the traditional electricity market, while accounting for physical grid constraints. The scheme enables small-scale prosumers to reach critical mass and trade energy units beneficially. Even though policies for long-term investments in RES (i.e., the RES capacity market) are outside the scope of this paper, there is a close interrelation between the short-term and the long-term market: the most profitable the short-term market is for RES, the easier it becomes to design attractive long-term investment policies. Table I summarizes market issues related to different algorithms used for forming the VAs.

III. PROBLEM FORMULATION DEFINITION

A. Prosumers' Level

We assume that prosumer $p_i, i = 1, 2, \ldots, N$, can offer to the market up to x_i^{max} RES units, called the maximum capacity of p_i. The quantity x_i^{max} varies with time and depends on a prosumer's nominal production capacity and the weather conditions at the given period t.

For a profitable business, a prosumer has to be able to recover its amortized investment costs, increased by a small Return On Investment (e.g., ROI=7%), plus fixed operational costs and any variable operational costs (mainly for fuel, if applicable). In the following, we assume that all these costs are included in the ATC. Variable operational costs are negligible for some RES producers, such as photovoltaic, since such type of prosumers use no fuel. Function ATC(x_i) is decreasing with x_i up to x_i^{max}; after that point new investment is needed and ATC(x_i) exhibits a steep increase. Since new investments take months to materialize and we are interested only in short-term markets (day ahead, intra-day, etc.), we ignore the possibility of capacity expansion and assume that ATC(x_i) is decreasing with x_i and becomes infinite at $x_i = x_i^{max} + \varepsilon$.

It is important to note that the previous discussion assumes that it is feasible for p_i to deliver an amount x_i of energy to the grid at a given region r, in the sense that *physical constraints* posed by power flow equations involving the capacity of the grid are satisfied. A prosumer supplies energy to the grid through a substation physical connection. In case x_i^{max} cannot be supported due to physical limitations, prosumer p_i will not be allowed to participate in the VAs or it will participate up to a production level smaller than its capacity x_i^{max}. Usually, the Distributed System Operator (DSO) runs Distributed Management System (DMS) tools to monitor and control the entire distribution network. The DSO is assumed to be aware of the ability of the grid to exchange energy with a particular prosumer. Generally, the assignment of prosumers to clusters in a given region r has to respect physical constraints posed by the DSO, related to the degree to which the grid can support power exchanges in that region.

Let us denote as I_i a factor indicating the ability of the grid to receive the energy units of prosumer p_i. Values of I_i close to zero mean that the grid has no availability in receiving energy units from p_i, while values of I_i close to one indicate grid availability in absorbing nearly all the x_i^{max} energy units. The *effective* capacity x_i^{cap} of p_i is thus defined as

$$x_i^{cap} = I_i \cdot x_i^{max} \tag{1}$$

Let us denote by $d_i(x_i, r)$ the per unit price prosumer p_i desires in order to deliver x_i energy units to the grid. In this desired price, one should include, in addition to the ATC, an overhead cost $\mu_i(r)$ for the DSO that depends on the physical location of p_i and the region r where the energy is demanded. Thus, p_i asks for a total *desired price*

$$d_i(x_i, r) = ATC(x_i) + \mu_i(r) \tag{2}$$

Eq. (2) means that if prosumer p_i offers its capacity x_i^{cap} at region r, its desired price will be $d_i^{cap} \equiv d_i(x_i^{cap}, r)$. The desired price is just enough for p_i to run a profitable (viable) business, including a small ROI. In a similar notion we denote as $\lambda_i(x_i, r)$ the marginal cost (MC) of a prosumer, generating x_i energy units plus the overhead $\mu_i(r)$.

$$\lambda_i(x_i, r) = MC(x_i) + \mu_i(r) \tag{3}$$

For small x_i, economic theory [32] states that $\lambda_i(x_i, r) < d_i(x_i, r)$; For notational convenience we have suppressed the dependence on the time period t, and we will also usually suppress the dependence on region r. We also assume that the overhead cost $\mu_i(r)$ has been added to all prices.

B. Virtual Association Level

Let us denote by V_i the i-th VA. All members of V_i share a common price λ_{V_i} and have total effective capacity.

$$C_{V_i} = \sum_{j \in V_i} x_j^{cap} \tag{4}$$

To maximize prosumers' profit, we take $x_j \equiv x_j^{cap}$, since we have assumed that $d_j(x_j)$ of Eq. (2) is a decreasing function of x_j up to x_j^{cap}.

A VA is called feasible if it satisfies the demand, i.e., $C_V = D$. Otherwise, when $C_V < D$, the VA is called infeasible. The VAs are formed through a matching algorithm (i.e., a suitable market policy) so that the overall RES supply, denoted by SP, equals the demand D. Let us assume that after the application of a matching algorithm, K feasible VAs (clusters) have been created and are ordered in terms of their offered prices as $\lambda_{V_1} \leq \lambda_{V_2} \leq \cdots \leq \lambda_{V_K}$. Thus, V_1 is the most competitive (cheapest) association, V_2 the next one in competiveness, etc. We call V_{K+1} the cluster containing the remaining prosumers of capacity $C_{V_{K+1}} < D$.

Variable C_{V_i}refers to the *maximum energy capacity* that association V_i can offer. This amount deviates from the *assigned capacity* D_{V_i} that V_i is actually *assigned* in the market, which will depend on the sharing policy we use, as will be described shortly. Since the $K+1$ VAs should share a total amount D of energy, we have

$$\sum_{i=1}^{K+1} D_{V_i} = D. \tag{5}$$

Given the values of D_{V_i} and λ_{V_i}, the equilibrium price offered to the market will be

$$\lambda_{RES} \equiv \frac{1}{D} \sum_{i=1}^{K+1} \lambda_{V_i} \cdot D_{V_i}. \tag{6}$$

Clearly, the capacity assigned to V_i is less than its maximum capacity, $D_{V_i} \leq C_{V_i}$. The main purpose of the different sharing algorithms (can also be viewed as market models) that we will propose will be to define the actual amounts D_{V_i} assigned to each V_i, $i = 1, 2, \ldots, K+1$. In this paper, four different sharing algorithms (sharing policies) are investigated, the formulations of which are described below.

The Winner Takes All Policy: Under this sharing scheme, only the most competitive VA, namely V_1, is assigned to deliver energy to the market. Thus, with this policy we have

$$D_{V_1} = D, D_{V_i} = 0, \text{ for all } i \neq 1, \tag{7}$$

Eq. (7) indicates that in this case the requested demand D is covered exclusively by the most competitive cluster, while the remaining VAs are excluded from the market.

Equal Volume Sharing Policy: With this sharing scheme, all VAs get an equal share of the RES market demand, regardless of their competitiveness. Thus,

$$D_{V_i} = D_{V_j}, \text{ for all } i, j. \tag{8}$$

Equal Income Sharing Policy: Again, all clusters participate in the marker but their actual assigned amount is proportionally adjusted based on the common price of the VA. This means that the income $\lambda_{V_i} \cdot D_{V_i}$ is the same for all V_i:

$$\lambda_{V_i} \cdot D_{V_i} = \lambda_{V_j} \cdot D_{V_j}, \text{ for all } i, j. \tag{9}$$

Rank-Based Fair Sharing Policy: This scheme favors more strongly (and to a degree that is parametrized) the more competitive clusters against less competitive ones, in the following way. Higher profits are allocated to more competitive VAs compared to the Equal Income Sharing policy, while the opposite holds for less competitive VAs. The Rank-based Fair Sharing algorithm uses the competitiveness order to distribute the demand among the VAs in a way that

$$\lambda_{V_1} \cdot D_{V_1} > \lambda_{V_2} \cdot D_{V_2} > \cdots > \lambda_{V_{K+1}} \cdot D_{V_{K+1}} \tag{10}$$

More details on the different sharing policies among VAs will be given in Section VI.

C. Implementations

As already mentioned, Virtual Associations were introduced in the European research project VIMSEN [19] as a new market model to internalize the positive externalities of RES. This paper presents the research algorithms used in VIMSEN to form VAs. VIMSEN delivers, among others, the *VIMSEN scheduler*, a Web-based interface acting as an ICT platform mediator between the small-scale prosumers and the electricity market. The platform communicates, through high speed 4G networks, with prosumers' gateways to collect aggregate production/consumption data. The dedicated VIMSEN gateway is also enriched with local forecasting capabilities in order to increase prosumers' reliability in estimating the x_i^{max}'s.

Each prosumer p_i declares a desired price d_i^{cap}on the Web portal. VIMSEN platform also communicates through a service oriented architecture (SOA), with the Distributed Management System (DMS) toolkit of the DSO to get information on the p_i 's topology and the physical constraints of the distribution grid, thus calculating the values of I_i used in Eq. (1). Upon a request for a RES demand by the electricity market, the VIMSEN scheduler creates in real-time the VAs. Prosumers within cluster V_i receive a common price λ_{V_i} for the energy RES units they offer. The adopted sharing algorithm runs first to determine the energy shares D_{V_i} that each VA receives. Then, each prosumer within a VA gets a delivery share proportionally to its initially declared price.

The VAs are optimally created by the VIMSEN scheduler and operates autonomously. In case a prosumer is not willing to participate into the VA, it refuses the offer and new clusters are formed. Our approach is highly distributed, meaning that there is no 'super-user" that controls the others within a VA. The following section considers the competition among prosumers when forming VAs and when acting independently.

IV. Min-Max Optimization to Form the VAs – Competition at the Prosumers' Level

A. The Non-Association (Independent Prosumers) Case

We first assume that each prosumer p_i acts independently, with no associations allowed. We assume numerous small-scale independent prosumers p_i, with $x_i^{cap} \ll D$ for all i, who react to bids from the RES market operator agent. Let us denote by λ_{MC}^n the price offered by the RES agent to prosumers during the n-th iteration of the algorithm. The response of p_i to the offered price λ_{MC}^n is an energy quantity x_i^n, such that

$$x_i^n \equiv x_i\left(\lambda_{MC}^n\right) \leq x_i^{cap} \;\; i = 1, 2, \ldots, N \text{ with} \tag{11a}$$

$$\lambda_{MC}^n \equiv MC\left(x_i^n\right) + \mu_i, \tag{11b}$$

where $MC(x_i^n)$ is the marginal cost of p_i in producing x_i^n units of RES energy. At $n+1$ iteration, λ_{MC}^{n+1} is updated as

$$\lambda_{MC}^{n+1} = \lambda_{MC}^n + \eta \cdot \left(D(r) - \sum_{i=1}^{N} x_i^n\right) \tag{12}$$

Variable η is a scalar that regulates the rate of update of the price. From Eq. (12) we see that that the price increases when the supply of RES producers at that price does not meet the requested demand, and decreases otherwise. The algorithm terminates when $SP^n = \sum_{i=1}^{N} x_i^n = D$, reaching the optimal price λ_{MC}. The aforementioned market model handles prosumers as small independent entities who compete against each other. Usually, the Buyer (i.e., the traditional market) is a big player, aware of the market, who presses RES prosumers to sell their energy at a price close to their marginal cost.

B. The Virtual Association Case

In this section, we present an algorithm for creating VAs, through a *min-max optimization process*; a) VAs operate at the *minimum* possible price (increasing their competitiveness), and b) *maximization* of cluster members' benefits is accomplished.

Let us denote by $V(n)$ a VA created at the n-th iteration of the algorithm, where all members of $V(n)$ share a common price $\lambda_{V(n)}$ and have total capacity

$$C_{V(n)} = \sum_{i \epsilon V(n)} x_i^{cap} \tag{13}$$

Then, the following cases are considered.

1) The Case of Infeasible Associations: Let us first consider an infeasible association $V(n)$ of total capacity $C_{V(n)} < D$ at the n-th iteration when all members operate at their capacity x_i^{cap}. Since $x_i^{cap} \ll D$ a VA consists of several prosumers p_i of different desired prices d_i^{cap}. The common price $\lambda_{V(n)}$ of a VA equals the maximum desired price for all $p_i \in V(n)$, since at this price, all prosumers are willing to offer their maximum capacity,

$$\lambda_{V(n)} = \max_{i \epsilon V(n)} d_i^{cap}. \tag{14}$$

At iteration $n+1$, a new prosumer p_j will be added to $V(n)$, as long as $C_{V(n)} < D$, to make it feasible. Prosumer p_j offers to the cluster an amount of energy x_j^{cap} at a price d_j^{cap}. When the prosumer is added, the association $V(n+1) = V(n) \cup \{j\}$ will have capacity and price given by

$$C_{V(n+1)} = C_{V(n)} + x_j^{cap} \text{ and}$$
$$\lambda_{V(n+1)} = max\left\{\lambda_{V(n)}, d_j^{cap}\right\}, \tag{15}$$

Respectively. Eq. (15) implies that $V(n)$'s competitiveness increases when the newly added prosumer p_j is the one offering the minimum price over all the available ones, i.e., when

$$\hat{j} = arg \min_{j \notin V(n)} d_j^{cap} \tag{16}$$

In case more than one equally competitive prosumers are available, the one of maximum effective capacity is preferred since this choice increases VA competiveness.

2) The Case of Feasible Associations: Let us now consider a feasible VA, i.e., $C_V = D$. Then, there is no benefit for the prosumers in V to add more members, because:

i) If the new prosumer p_j has desired price $d_j^{cap} \leq \lambda_V$, the common VA price will remain unchanged [see Eq. (15)], but the remaining prosumers p_i will then be forced to operate at a production lower than x_i^{cap}, since $C_V > D$, reducing their profits.

ii) If the new prosumer p_j has $d_j^{cap} > \lambda_V$, then the VA's competitiveness is reduced, since its price will increase.

3) The Min-Max Algorithm: Based on the above, we introduce a min-max optimal algorithm for creating VAs, offering the *minimum possible price at the maximum prosumers' benefits*. The algorithm starts with no existing VAs. Then, the optimal decision for each prosumer is to make an association with the most competitive (cheapest) available prosumer since this choice maximizes its competiveness. As a result, the cheapest prosumers join together until their VA satisfies the demand. Note that demands for different regions may result in different VAs due to the different $\mu_i(r)$ and the different physical constraints (different prosumers that are allowed to participate). A summary of the min-max algorithm for forming the VAs is presented in Table II.

The output of the min-max algorithm is a set of VAs, ranked according to their price (competitiveness); V_1 is the most competitive VA, V_2 the second one, while V_{K+1} is the cluster containing the remaining prosumers.

V. Virtual Association Competition Policies

The exact way the market volumes are assigned is an important factor for the stability of the RES split market and affects the equilibrium of the RES price. In this section, we consider four demand sharing policies, namely: Winner Takes All, Equal Volume sharing, Equal Income sharing, and Rank-based Fair sharing. These policies can be unified as follows.

After the clusters $V_i, i = 1, 2, \ldots, K+1$, have been found, we express the amount D_{V_i} assigned to cluster V_i as

$$D_{V_i} = r_{V_i} \cdot C_{V_i} \tag{17}$$

TABLE II
SUMMARY OF THE MIN-MAX ALGORITHM USED TO FORM VAS

Initialization	***Declare pairs of (x_i^{cap}, d_i^{cap}) for each prosumer:*** 1. *R*egistered prosumers declare to the VIMSEN ICT platform an amount of RES energy units x_i^{max} at a desired price d_i^{cap}, *i*=1,2,…,*N*. 2. The ICT mediator tailors the x_i^{max} units to the physical network constraints- see Eq. (1)- to find x_i^{cap}, for *i*=1,2,…,*N*.
Step 1	***Create a ranked list of prosumers***: Rank the *N* registered prosumers according to their declare price d_i^{cap}in an ascending order and then rank them according to their energy units x_i^{cap} in a descending order.
Step 2	***Create the VA clusters***: Take the first ranked prosumers, the ones of the cheapest price and of maximum energy units, to form the first VA. Terminate in case that the capacity of the prosumers in the VA cluster satisfies the demand, $C_V = D$, or in case that no prosumers are available
Step 4	**Remove and Continue**: Remove the prosumers chosen for the VA from the ranked list and if prosumers are available go to the Step 2 to form additional VAs.

where r_{V_i} is the contribution factor of cluster V_i. In an *n-weighted fair sharing scheme*, we set

$$r_{V_i} = \frac{\left(1/\lambda_{V_i}\right)^n}{\sum_i \left(1/\lambda_{V_i}\right)^n} \tag{18}$$

where n in [0, 8) is a coefficient to be discussed shortly. The n-weighted fair sharing concept was proposed in [34] for grid computing, following ideas introduced earlier for traffic sharing and statistical multiplexed networks [35].

The Winner Takes All Policy: This corresponds to choosing $n \to \infty$ in Eq. (18). In this policy, only the most competitive VA is selected to deliver the RES demand. Thus, V_1 is assigned all the RES market share, while the remaining VAs are excluded from it. A disadvantage of the Winner Takes All policy is that losing prosumers, i.e., all $p_j \notin V_1$, receive no profit. Therefore, they may change their strategy and instead of asking for their desired price (that covers ATC), they may decide to sell at smaller prices, which through competition will eventually equal their marginal cost MC. Since MC<< ATC for RES, selling price at MC will not be viable in the long-term. Another limitation is that the Winner Takes All strategy reduces the number of surviving prosumers, eventually leading to lower competition (see Section VI). For this reason, we propose alternative policies where the winning VA shares the demand with other VAs:

The Equal Volume Sharing Policy: In this case, all clusters get an equal share of the RES market demand, irrespectively of their offered price [see Eq. (8)], which corresponds to choosing *n*=0 in Eq. (18). Such a sharing policy provides no incentives for prosumers to improve their competitiveness. Using Bertrand competition model we can show that this policy presents instabilities in terms of the Nash equilibrium of the RES price achieved. This is mainly because less competitive prosumers receive higher income than more competitive ones.

The Equal Income Sharing Policy: This corresponds to setting $n = 1$ in Eq. (18). In this case, VAs get a market share inversely proportional to their offered price [see Eq. (9)]. The average price offered to the market is the harmonic mean of the cluster prices. This sharing algorithm results in marginal stability, since the prosumers tend not to change their behavior at the next bidding intervals.

Other values of n in Eq. (18) are also possible leading to different sharing policies. An alternative sharing scheme that includes an additional parameter is described next.

Rank-Based Fair Sharing: The algorithm allocates the amounts D_{V_i} based on the ranking order of the clusters with respect to their prices so as to yield

$$\lambda_{V_1} \cdot D_{V_1} \leq \cdots \leq \lambda_{V_{K+1}} \cdot D_{V_{K+1}}.$$

This way, the most competitive cluster (ranked 1) is more strongly favored against less competitive ones, receiving more income. More specifically, initially, a weight w_{i} is assigned to the VA ranked i based on its competitiveness ranking:

$$w_i = \frac{1}{\lambda_{V_i}} \cdot \delta^{(K+1)-i} \tag{19}$$

where $\delta > 1$ is a constant parameter that determines the importance of the competitive order in the fair sharing algorithm. Values of δ close to one tend to Equal Income sharing, while large values of δ mean that competitive VAs are more strongly favored against less competitive ones. Note that in the equal Income Sharing policy ($n = 1$) each VA had a weight $w_i = 1/\lambda_{V_i}$, while in the rank-based fair sharing policy the weights of the most competitive VAs take larger values, allocating more income (and even more profit) to competitive VAs.

Each VA has a total amount C_{V_i} of energy it can offer, where $C_{V_i} = D$ for all $i \leq K$ and $C_{V_{K+1}} < D$ for the last association. Given the weights w_i, t he Weighted Fair Sharing (WFS) algorithm, adopted from the computer network field [34], is used to determine the amounts D_{V_i} assigned to each VA. WFS uses the weights w_i defined in (19). At the first stage, the algorithm estimates the amounts D_{V_i} using a weighted sharing scheme. In subsequent iterations, the leftovers are further allocated to the unsatisfied VAs.

Fig. 2 describes the main stages of the WFS algorithm proposed to share the demand across multiple VAs.

***Stage #1*:** At stage 1, a set of K+1 clusters (VAs) are formed and are ranked with respect to their common price as $\lambda_{V_1} \leq \lambda_{V_2} \leq \cdots \leq \lambda_{V_K}$. The most competitive association V_1 offers to the market the requested quantity D at a price λ_{V_1}. If we stopped here, it would be the Winner Takes All policy with the aforementioned disadvantages.

***Stage #2*:** At stage 2 of the algorithm, the winning VA V_1 decides to offer a share $D_{V_2}$to the second most competitive association V_2 to handle the risk of losing the bid, since all $p_i \in V_2$ could choose to operate at their MC. Cluster V_2 accepts the offer, gaining a revenue of $\lambda_{V_2} \cdot D_{V_2}$.

***Final Stage*:** The aforementioned process is repeated for all the VAs, with each V_i receiving a market volume of D_{V_i}.

Table III summarizes the main steps of how VAs participate in the market using the rank-based fair sharing algorithm.

VI. ANALYSIS OF COMPETITION AMONG PROSUMERS AND AMONG VAS BASED ON BERTRAND MODEL

In this section, we analyze the competition among prosumers and among VAs based on the principles of Bertrand

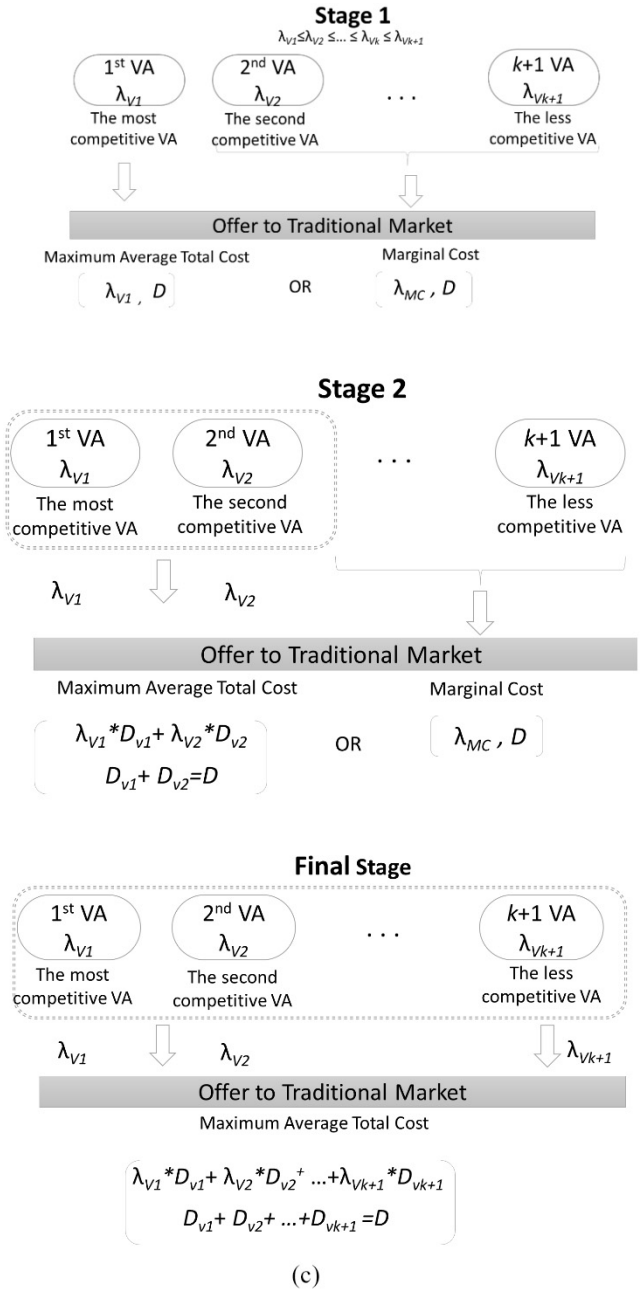

Fig. 2. The workflow of the proposed fair sharing algorithm among VAs.

TABLE III
MAIN STEPS OF HOW THE VAs PARTICIPATE IN THE MARKET USING RANK-BASED FAIR SHARING POLICY

Step 1	***Each association V_i declares a price λ_{V_i}:*** The prices λ_{V_i} are set according to Eq. (14) so to maximize the profit of the prosumer members of V_i.
Step 2	***Weight Assignment:*** For each association V_i a weight w_i is defined using Eq. (19).
Step 3	***Fair Sharing:*** A demand share D_{V_i} is allocated to each VA using WFS algorithm.
Step 4	**The equilibrium price:** The equilibrium price, given by Eq. (6), is delivered to the traditional market for the D RES units.

Model of Duopolies [19]. The Bertrand model describes a situation where two players reach a state of Nash equilibrium by setting different prices [31].

A. Competition Among Prosumers

At this level of analysis, competition is among prosumers who constitute the game players. Prosumer p_i can offer x_i^{cap} RES energy units at a price d_i^{cap}. Prosumers compete against each other to maximize their profits by appropriately setting the price d_i^{cap} for x_i^{cap}.

Assuming that more competitive VAs receives more profit (which is true for the rank-based fair sharing policy), prosumers with lower declared price d_i^{cap} are favored against more expensive ones. This is because they join together to form a more competitive VA until the requested demand is satisfied. Therefore, the best option for a prosumer is to obtain the best possible ranking order he/she can, while not losing money, given that he/she does not know the offered prices of other prosumers, thus optimizing his/her capability of being grouped to a competitive VA and receive higher profit.

Theorem 1: The Nash equilibrium for prosumers is to set their price to maximize profit as

$$d_i^{cap} = c_i, \quad \text{for all } i \tag{20}$$

only if

i) demands are allocated among VAs so that $\lambda_{V_1} \cdot D_{V_1} > \cdots > \lambda_{V_{K+1}} \cdot D_{V_{K+1}}$ (i.e., more competitive VAs get more income than less competitive ones) and

ii) the higher ranked (less priced) prosumers join together to form the more competitive VA – the min-max algorithm.

Variable $c_i \equiv ATC(x_i^{cap})$ is the total average cost for the production of x_i^{cap} energy units.

Proof: Eq. (20) is derived by contradiction. If price d_i^{cap} is set greater than c_i, i.e., $d_i^{cap} > c_i$, then prosumer p_i will be assigned to a less competitive association, which consequently will reduce his/her profit since $\lambda_{V_1} \cdot D_{V_1} > \cdots > \lambda_{V_{K+1}} \cdot D_{V_{K+1}}$. Instead, if price d_i^{cap} is set less than c_i, prosumer p_i will receive no profit since his profit is $\Pi_i = d_i^{cap} \cdot x_i - c_i \cdot x_i$. ■

B. Competition Among VAs

In this level of analysis, competition is among VAs, now constituting the game players. Each VA V_j sets a common price λ_{V_j} for all its members for the RES units it offers. Here, VAs compete against each other to maximize the profit of their members. This means that they set the maximum possible price, without however, spoiling their competitiveness order with respect to the other VAs (assuming that first ranked VAs receive larger shares than the remaining ones). The analysis followed defines (i) the way the common price λ_{V_j} is determined and (ii) the way the sharing algorithm used to allocate the demands D_{V_j} affects VA competition.

Regarding the way the common price λ_{V_j} is determined, we have the following theorem (note that Eq. (21) verifies the min-max algorithm used in Section V to form VAs).

Theorem 2: The Nash equilibrium for a virtual association V_j is to set its price to maximize its members' profit as

$$\lambda_{V_j} = \max_{i \in V_j} c_i^{(j)} \equiv c_{max}^{(j)} \tag{21}$$

only if demand sharing is allocated among the VAs in a way that $\lambda_{V_1} \cdot D_{V_1} > \cdots > \lambda_{V_{K+1}} \cdot D_{V_{K+1}}$.

In Eq. (21), $c_i^{(j)}$ is the ATC cost of the i-th prosumer in the j-th VA, that is, $p_i \in V_j$.

Proof: The proof of Eq. (21) will be done by contradiction. If V_j declares a price greater than $c_{max}^{(j)}$, then V_j may lose its competitiveness against V_{j+1} and thus receive a smaller share and a smaller profit for the V_j members (since $\lambda_{V_1} \cdot D_{V_1} > \cdots > \lambda_{V_{K+1}} \cdot D_{V_{K+1}}$). On the other hand, if V_j sets a price smaller than $c_{max}^{(j)}$, its prosumer members will receive less profit than they could get. Indeed, V_j could increase it price without spoiling its competitiveness order since the next VA V_{j+1} cannot declare a price smaller than $c_{max}^{(j)}$ (such a choice for V_{j+1} will result in zero profit for all its members since $c_{min}^{(j+1)} > c_{max}^{(j)}$, where $c_{min}^{(j)} = \min_{i \in V_j} c_i^{(j)}$). Therefore, $\lambda_{V_j} < c_{max}^{(j)}$ is not an optimal choice for V_j. In the above analysis, we assume that a VA is not aware of the prices of the other VAs, since otherwise the price should be set equal to $c_{min}^{(j+1)}$. ■

1) Equal Volume Sharing Policy: With Equal Volume Sharing, VAs are allocated equal shares, $D_{V_i} = D_{V_j}$, for all i, j [see Eq. (8)], and since $\lambda_{V_1} \leq \cdots \leq \lambda_{V_K}$, the more costly ones receive more revenue

$$\lambda_{V_i} \cdot D_{V_i} \leq \lambda_{V_j} \cdot D_{V_j}. \tag{22}$$

Eq. (22) states that the optimal choice for V_j is to increase its price λ_{V_j} since this choice maximizes its profit. This results in a VA competition where each player sets higher price values to get more profit, without losing share. Thus, Equal Volume Sharing does not satisfy the conditions of Eqs. (20) and (21).

2) Equal Income Sharing Policy: In the Equal Income Sharing policy, the VAs are allocated market shares inversely proportional to their offered prices, and the resulting income is the same for all V_j, i.e., $\lambda_{V_i} \cdot D_{V_i} = \lambda_{V_j} \cdot D_{V_j}$, for all i, j [see Eq. (9)]. In this policy, the income of a VA is independent of the price λ_{V_j} it declares. Therefore, each VA can set arbitrary prices since this choice does not affect the income (and profit) of its members.

3) Winner Takes All: In this policy, the most competitive virtual association V_1 receives all the share, and the remaining VAs get no profit. For V_1 the optimal choice is to set its common price $\lambda_{V_1} = c_{max}^{(1)}$ [see Eq. (21), assuming that V_1 is not aware of the prices of the other VAs], since in this way it can remain the most competitive one while maximizing its profit.

For the remaining virtual associations V_j, $j \neq 1$ there is no way to profitably participate in the market and receive a share. The ATC for prosumers in such VAs is greater than that of V_1, i.e., $c_i^{(j)} > c_{max}^{(1)}$ for $j \neq 1$. The Winner Takes All policy satisfies the conditions of Eqs. (20) and (21) and an equilibrium exists. However, Winner Takes All policy promotes only the most competitive prosumers who share all profit among themselves. Prosumers outside V_1 receive no profit and eventually perish. Thus, the most competitive prosumers end up monopolizing the market and having the ability to manipulate it.

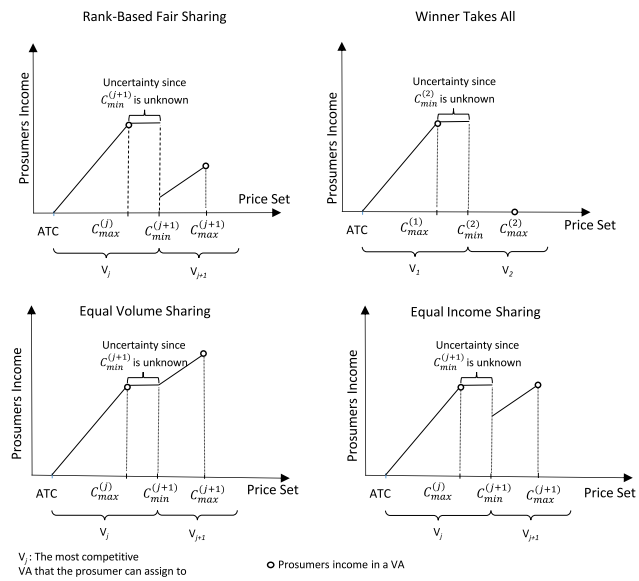

Fig. 3. A graphical representation of the competition model for the different scenarios investigated to form the VAs.

4) Rank-Based Fair Sharing: This policy allocates shares so that the more competitive VAs receive larger income than the less competitive ones.

Theorem 3: Rank-based Fair Sharing policy satisfies condition

$$\lambda_{V_1} \cdot D_{V_1} > \cdots > \lambda_{V_{K+1}} \cdot D_{V_{K+1}}$$

allocating more income (and even more profit) to the most competitive VAs.

Proof: With Rank-based Fair Sharing, each VA has weight given by (19). The demand D is first divided into portions $Q = D/q$, with $q = \sum_i w_i$, and V_i receives a portion $w_i \cdot Q$. of the total share. Since $w_i/w_{i+1} = \delta \cdot \lambda_{V_{i+1}}/\lambda_{V_i}$, we have

$$\frac{\lambda_{V_i} \cdot D_{V_i}}{\lambda_{V_{i+1}} \cdot D_{V_{i+1}}} = \frac{\lambda_{V_i} \cdot w_i \cdot D_{V_i}}{\lambda_{V_{i+1}} \cdot w_{i+1} \cdot D_{V_{i+1}}} = \delta > 1, \tag{23}$$

yielding $\lambda_{V_1} \cdot D_{V_1} > \cdots > \lambda_{V_{K+1}} \cdot D_{V_{K+1}}$. ■

Consequently, Rank-based Fair sharing satisfies the conditions of (20) and (21). Particularly, at the level of prosumers, each p_i sets a price $d_i^{cap} = c_i$ in order to be positioned at the best ranking order it can be, and thus joining the most competitive VA it can. Other choices for a prosumer deteriorate its order positioning and thus its profit, given that he does not know the prices of the other prosumers. In the level of VA, the best choice is to set the common price of a VA equal to the maximum Average Total Cost $c_{max}^{(j)}$ over all prosumers belonging to this VA. Since Rank-based Fair Sharing allocates shares so to satisfy $\lambda_{V_1} \cdot D_{V_1} > \cdots > \lambda_{V_{K+1}} \cdot D_{V_{K+1}}$, any other choice of a VA is not profitable for its prosumers.

Fig. 3 graphically explains the competition model for the different policies discussed. Particularly, with Rank-based Fair sharing, initially each prosumer sets his/her desired price equal to their ATC cost to maximize their competitiveness without losing money. Then, the price a prosumer gets equals the maximum price within his/her VA, assuming that prices outside the VA are unknown. This policy maximizes the profit of the

prosumer and verifies the min-max algorithm adopted. A prosumer cannot (greedily) increase his/her desired price above $c_{max}^{(j)}$, without undertaking the risk (not knowing the other prosumers' prices) of being assigned to a less competitive cluster and thus receiving less profit. Instead, with Equal Volume sharing, the income of less competitive prosumers is greater than that of more competitive ones as depicted in Fig. 3. In the Equal Income sharing policy, prosumers' income remains the same regardless of the price set. Finally, in the Winner Takes All policy only prosumers in the most competitive VA receives profit, forcing the remaining ones to perish.

The benefit of Rank-based Fair Sharing algorithm is that all prosumers receive a profit according to their ranking competitiveness. Less competitive prosumers can gradually accumulate some profit to invest on innovative infrastructures so as to become more competitive in subsequent bidding cycles and thus gain more money. As a result, the Rank-based Fair Sharing promotes competition without forcing the less competitive prosumers (usually the smallest ones) out of the market.

C. Validity of the Rank-Based Fair Sharing Scheme

Let us assume that $D_{V_i} = r_{Vi} \cdot C_{V_i}$ where $0 < r_{Vi} < 1$ and $C_{V_i} = D$, for $i = 1, \ldots, K$, while $C_{V_{K+1}} < D$. Since the VAs V_i are ordered in terms of offered prices ($\lambda_{V_i} \leq \lambda_{V_{i+1}}$) and the order is not changed, we have that $r_{Vi} \geq r_{Vi+1}$ under the Rank-based Rair Fair sharing. That is, the less competitive a cluster is, the smaller is the share it receives. For the policy to be profitable for the remaining prosumers (who have the option to participate at their marginal cost, if excluded) we should have that

$$r_{Vi} > \frac{\lambda_{MC}}{\lambda_{V_i}} \tag{24}$$

where λ_{MC} is the marginal cost of the prosumers excluded from the winning cluster and λ_{V_i} the common price of V_i. If λ_{MC} were known for all prosumers, optimal shares could be defined as $\hat{r}_V i = \lambda_{MC}/\lambda_{Vi}$. In our distributed case, however, prosumers are unaware of λ_{MC}, which is dynamically modified in each period (hour–ahead biding). For this reason, the sharing algorithm takes place to "fairly" re-allocate shares among VAs. The exact values of r_{Vi} are determined by parameter δ.

From Eq. (15), it is clear that $\lambda_{MC} \ll \lambda_{V_i}$ as λ_{V_i} is the maximum of the desired prices among all prosumers in V_i. Consequently, shifting only small shares of the winning clusters to the remaining ones is adequate to "convince" the losing parties not to participate in the market at their MC. Since $\lambda_{V_i} \leq \lambda_{V_{i+1}}$, the inequality $r_{Vi} \geq r_{Vi+1}$ is also valid, meaning that the less competitive a cluster is, the smaller is the share given to it.

VII. Experiments

A. Experimentation Setup

In our experiments, we used realistic production patterns from solar and wind generators [19], [36]–[38]. In total 13,000 time series were used, each representing RES units

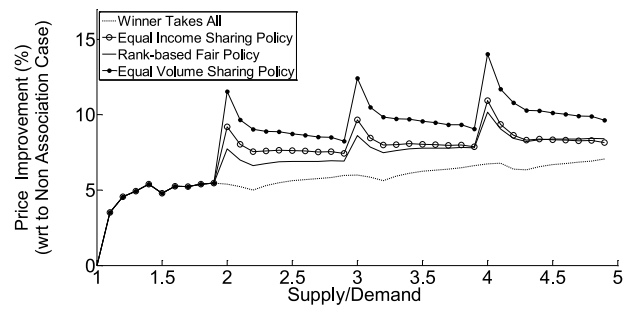

Fig. 4. Improvement (%) with respect to the non-association case. The price has been normalized versus the prices for the case of $SP = D$. We assume low standard deviation for the prosumers' desired price distribution.

that p_i offers to the market at certain time instances t, sampled, in our case, per hour. Each prosumer p_i sets a desired price for selling its surplus energy x_i^{cap}, subject to physical constraints [see Eq. (1)]. In the experiments, prices were taken to follow a normal distribution, the deviation of which defines price variability. Our VA formation algorithm takes as input the desired price d_i^{cap} and production x_i^{cap} declared by prosumer p_i. Then, the price and profit achieved by prosumers under our scheme and market model is evaluated and compared to those achieved under the non-association independent model. To estimate price λ_{MC} the production cost has to be modelled, which lies outside the scope of this paper. In our experiments, and only for comparison purposes, a Bernoulli distribution function is adopted to model the probability of a prosumer reacting to a price offered by the traditional electricity market.

B. The Effect of the Matching Algorithms to Form VAs on the RES Price

Fig. 4 depicts the percentage (%) improvement in the price attained for the prosumers when forming VAs model and under different sharing policies over the price achieved for them in the non-association case. These price improvements over the non-association case are the motivating factor for RES prosumers to invest and subscribe in the VA concept and participate in a RES split market. With current approaches, this motivation is provided through the subsidy FIT, which is not, however, a time varying policy. The % improvements are plotted versus different levels of *SP*/*D* ratio and for different sharing policies. All the results obtained assume a low standard deviation for the desired price. For comparative representation, Fig. 4 shows the results in the form of % improvements over the prices achieved when $SP = D$.

The best price improvement for prosumers is achieved under the Equal Volume Sharing policy, with the Equal Income Sharing policy coming next. However, these schemes are not stable in terms of the price equilibrium achieved. The Rank-based Fair Sharing algorithm simultaneously provides market stability and keeps the price higher as the supply increases compared to the non-association (independent prosumers) case. Additionally, the RES prices obtained by the Rank-based Fair Sharing algorithm are close to those provided by the other (unstable) sharing schemes. An instant peak in prosumers' price is noticed whenever a new feasible

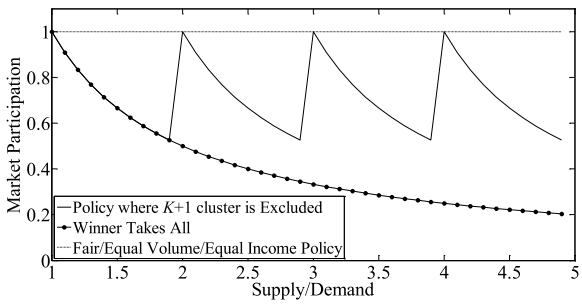

Fig. 5. Market participation vs. *SP/D* ratio for different clustering methods.

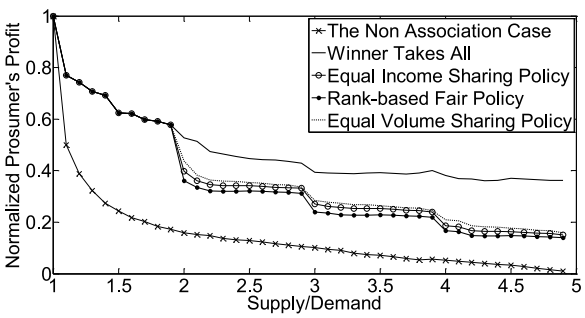

Fig. 6. Prosumers' profit normalized with respect to the profit achieved at s *SP=D* for different clustering approaches. We assume a low standard deviation as for the prosumers' desired prices. The profit has been estimated only over the prosumers that participate in the market.

cluster (VA) is formed, that is, when *SP /D* equals next integer value. As supply increases prosumers continue to receive higher price than in the non-association case, by participating in VAs.

C. The Effect of the Matching Algorithms to Form VAs on Prosumers Participation

Figure 5 depicts market participation, i.e., the percentage (%) of prosumers delivering energy to the market over all prosumers. As expected, market participation with the Winner Takes All policy is significantly lower than with the other policies, as many high cost prosumers are excluded from the market, receiving no profit at all. Instead, the other policies guarantee that most prosumers (except for those in V_{K+1}) participate in the market, even though with different shares. In this figure, we also provided comparisons with a policy where the last $K+1$ non-feasible cluster is excluded from the market. In that case, as a new feasible VA enters the market, participation increases to one, and then starts decreasing as the additional prosumers are unable to provide the requested demand D.

D. The Effect of Sharing Policy on Prosumers' Profit

In this subsection, the prosumers' profit is examined, obtained from Eq. (20). The profit is normalized with respect to that achieved when $SP = D$. The results are depicted in Fig. 6. The profit has been averaged only over the prosumers that participate in the market. For that reason, the Winner Takes All market model yields the highest prosumers' profit (for the prosumers who actually participate), since the few prosumers in the most competitive VA share the RES demand D.

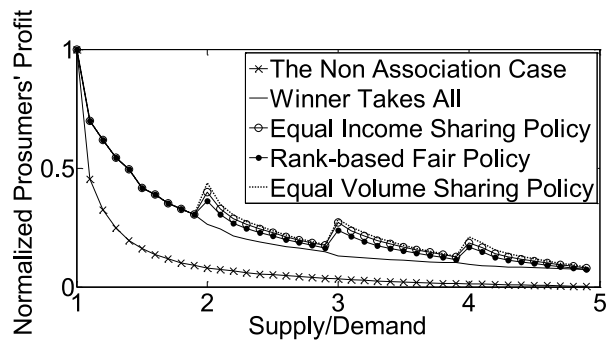

Fig. 7. Compensation of prosumers' profit of Figure 6 with respect to the market participation values of Figure 5, assuming all prosumers participate in the market.

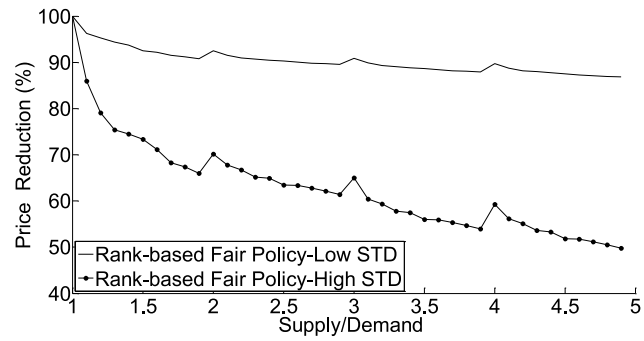

Fig. 8. The effect of the standard deviation of the prosumers' desired price on price achieved versus *SP/D* ratio. The results have been normalized at the price achieved when $SP = D$ regarding the Rank-based Fair Sharing policy.

The profit adjusted for market participation is shown in Fig. 7. It is clear that, under this metric, the Winner Takes All policy receives the lowest profit compared to the other clustering methods since with this policy many prosumers are excluded from the market, receiving no profit. Instead, the Equal Volume, Equal Income and Rank-based Fair Sharing policies yield almost the same adjusted profit, with Equal Volume Sharing being slightly more beneficial. However, only the Rank-Based Fair Sharing policy is stable with respect to the RES Nash equilibrium price, while also presenting almost similar behavior to the other schemes. In this figure, we have considered that all prosumers participate in the market.

E. Effect of Allocation Parameters and Input Data Properties

1) Standard Deviation: Figure 8 presents the effect of the standard deviation of the prosumers' desired prices on the prices achieved. Two cases are examined: high and low deviation. We observe that high deviation reduces the price achieved, since less costly prosumers are available. The results assume Rank-based Fair Sharing and have been normalized over the price achieved for $SP = D$.

2) Ranking Importance Parameter: Figure 9 depicts the effect of parameter δ [see Eq. (19)], which regulates the degree of sharing among different VAs in Rank-based Fair Sharing. Low values of δ make Rank-based Fair sharing similar to Equal Income sharing [$n = 1$ in Eq. (18)]. In our experiments

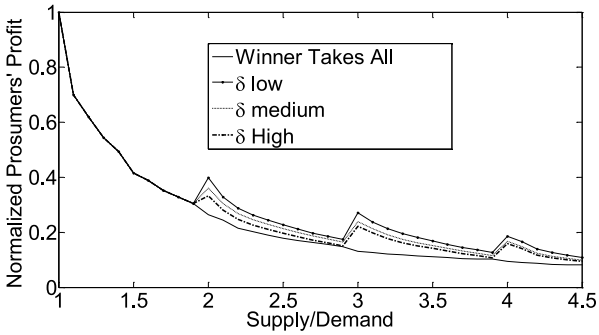

Fig. 9. The effect of parameter δ [Eq. (19)] on prosumers' profit versus *SP/D* ratio. The results have been normalized at the price achieved when $SP = D$ regarding the Rank-based Fair Sharing policy.

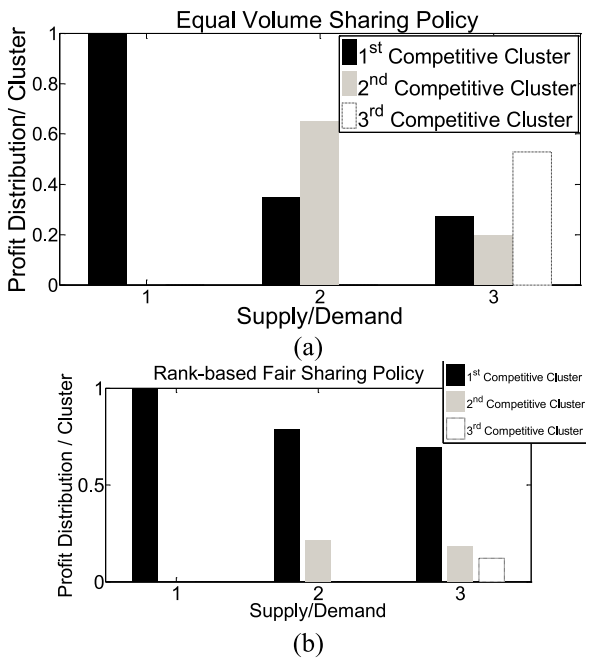

Fig. 10. Profit distribution over competitive clusters for different policies, (a) Equal Volume Sharing and (b) Rank-based Fair Sharing.

this low values of δ is set to 2. In contrast, high values of δ (in our case $\delta = 50$) yield a behavior resembling that of the Winner Takes All policy. This means that stability is achieved for a medium value of δ around 20.

F. Stability Effect

Although Equal Volume Sharing yields slightly higher prices and respective profits, it distributes unfairly the profit among prosumers. This results in unstable market behavior, as explained in Section VI and Section VII. This is because it does not penalize the less competitive clusters and gives no motivation for prosumers to become more efficient as presented in Fig. 10(a). Instead, the Rank-based Fair Sharing reasonably distributes the profit providing greater incentives to the more competitive VAs as shown in Figure 10(b).

G. Comparisons With Other Methods

This subsection presents comparisons between the Rank-based Fair Sharing schemes and the works of [10] and [11].

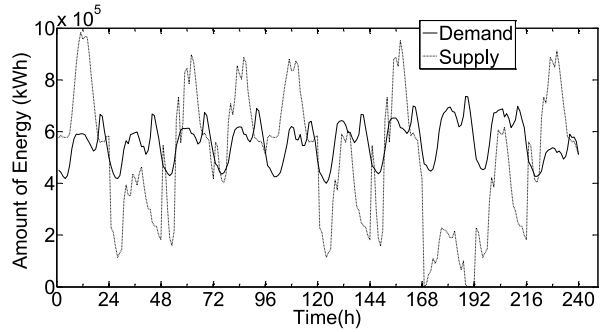

Fig. 11. Demand and supply vs. time for the experiments conducted.

TABLE IV
WEATHER CONDITIONS FOR THE TEN EXAMINED DAYS

Day No.	Description of the weather conditions	Day No.	Description of the weather conditions
1	Windy and sunny day	6	Medium winds and cloudy
2	Medium winds and cloudy	7	Variable winds and sunny
3	Variable winds and sunny	8	Low wind and rainy
4	High winds and sunny	9	Low wind and cloudy
5	High winds and sunny	10	Variable winds and sunny

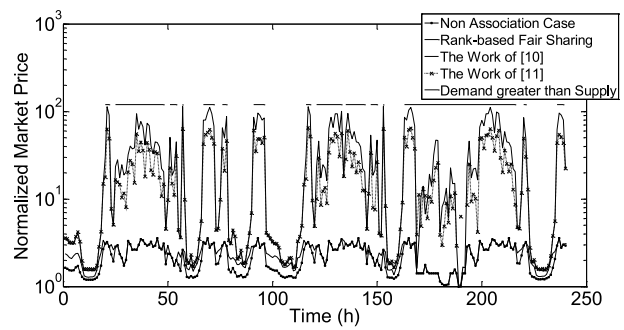

Fig. 12. Comparison of the normalized market price achieved versus time for i) the rank-based fair sharing policy, ii) the non-association case, iii) the work of [10] and iv) the work of [11].

The results were obtained using realistic demand-supply values for 10 consecutive days (Demand of Greece on 01-10/04/2015-hour ahead biding) as described in Table IV sampled per hour and under different weather conditions. Fig. 11 depicts the demand supply values for those 10 days.

Fig. 12 illustrates the market price, normalized with respect to the minimum price obtained under the non-association case, over the examined 10 days (240 hours). The Rank-Based Fair Sharing policy, the non-association case, and the methods of [10] and [11] are compared. The minimum price of the non-association case occurs at the time the maximum deviation of demand from supply is observed, namely at the 189th hour.

Fig. 13 depicts the prosumers' profit normalized with respect to the minimum profit of the non-association case, for these methods. We observe that both of the compared methods significantly increase RES price, especially when the demand exceeds supply, resulting in an unstable behavior. In contrast, our proposed market models stabilize the price, being saturated by the maximum desired price of the prosumers. In addition, the works of [10] and [11] yield lower profit for the

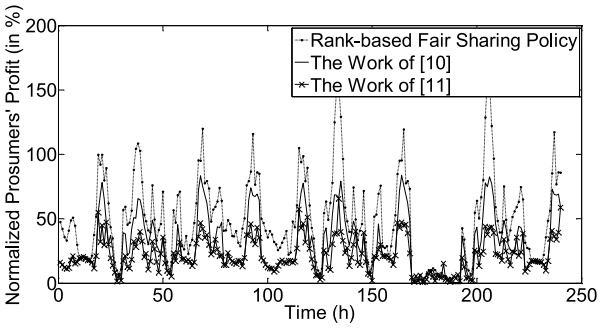

Fig. 13. Comparison of normalized prosumers' profit with respect to the minimum profit of the non-association case, vs time for i) the Rank-based Fair Sharing policy, ii) the non-association case, iii) the work of [10] and iv) the work of [11].

prosumers than the Rank-based Fair Sharing scheme, since they focus on maximizing aggregators' benefits, while our proposed market model optimizes prosumers' benefits. This is mainly because in the works of [10] and [11] the profit of the aggregator depends on the price offered to the traditional market. Therefore, the aggregator increases the price in order to maximize its profit. In the case of no competition among the aggregators (that is, for supply less than demand), the prices achieved increase significantly. Otherwise, the price is close to that our scheme, but is greater than that to account for the aggregator's profit. These results are in line with the arguments provided in [10], where a two-fold optimization strategy is presented for maximizing aggregator benefits.

VIII. Conclusion

RES provide positive externalities related to the environment and often to the proximity of production to consumption locations. To internalize these benefits, a RES split market model is proposed for each region and is integrated to the traditional energy market. If RES prosumers participated as individuals in a traditional market, they (being numerous and of small capacity) would have to sell their energy at the Marginal Cost of the marginal prosumer, which is significantly smaller than their Average Total Cost. To overcome this problem, we proposed virtual associations (VA) of RES units, and investigated different sharing policies (or market models) for the competition among VAs. The Winner Takes All policy allows only the most competitive cluster to deliver energy to the market, increasing the benefits for low cost prosumers but excluding the remaining ones and forcing them to perish. We examined three sharing policies to increase prosumers' participation in the market, namely the Equal Volume, the Equal Income and the Rank-Based Fair sharing policies. The first two policies do not sufficiently penalize high cost prosumers, resulting in an unstable market behavior. In contrast, Rank-Based Fair sharing simultaneously increases prosumers' participation and provides incentives for prosumers to become more competitive. Using the Bertrand Competition Model, we analyzed the aforementioned policies. Experimental results performed on realistic traces verify the previous conclusions and indicate the advantages of our market model and schemes over other compared methods.

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Nikolaos D. Doulamis (S'96–M'00) received the Diploma (Highest Hons.) and Ph.D. (Highest Hons.) degrees in electrical and computer engineering from the National Technical University of Athens (NTUA), where he is currently an Assistant Professor. He has authored over 55 (180) journals (conference) papers in the field of signal processing, computational intelligence. He has over 3000 citations and being involved in European projects. He was a recipient of many awards, such as the Best Greek Engineer Student, the Graduate Thesis Award, the NTUA's Best Young Medal, and the best paper awards in IEEE conferences. He has served as an Organizer and/or Program Committee Member of major IEEE conferences.

Anastasios D. Doulamis (S'96–M'00) received the Diploma (Highest Hons.) degree in electrical and computer engineering and the Ph.D. degree in video analysis from the National Technical University of Athens (NTUA) in 1995 and 2001, respectively. Until 2014, he was an Associate Professor with the Technical University of Crete. He is currently a Faculty Member of NTUA. He has authored over 200 papers receiving over 3000 citations. He was a recipient of several awards in his studies, including the Best Greek Student Engineer, the Best Graduate Thesis Award, and the National Scholarship Foundation Prize. He has also served as a Program Committee in several major conferences of IEEE and ACM.

Emmanouel (Manos) Varvarigos received the Diploma degree in electrical and computer engineering from the National Technical University of Athens, Greece, in 1988, and the M.S. and Ph.D. degrees in electrical engineering and computer science from the Massachusetts Institute of Technology in 1990 and 1992, respectively. He has held tenured faculty positions with the University of California, Santa Barbara, from 1992 to 1998, the Delft University of Technology from 1998 to 2000, and the University of Patras from 2000 to 2015. Since 2015, he has been a Professor of Electrical and Computer Engineering with the National Technical University of Athens, where he heads the High Speed Communication Networks Laboratory, and is involved in pioneering research and development projects at European level. He was also a Researcher with Bell Labs, and consulted with companies in the U.S. and in Europe.