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Electricity market policies for penalizing volatility and scheduling strategies: The value of aggregation, flexibility, and correlation

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HIGHLIGHTS

- A penalty policy for charging the day-ahead market contract violations is presented.
- Prosumer and Virtual Microgrid Association rescheduling strategies are studied.
- Insights for compensation policy for the prosumers' flexibility are provided.
- A study of the way penalty policy affects the prosumers' and Associations revenues is conducted.
- Effects of the prosumers' cooperation and correlation are studied.

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ABSTRACT

We consider small energy producers and consumers (i.e. prosumers), organized in groups in order to trade energy in wholesale markets as a single Virtual Microgrid entity. A market procedure is described, from the day-ahead to the balancing market, including load rescheduling procedures. Violations of day-ahead contracts are charged via a dynamic penalty policy in the form of a spread between buy and sell price of electricity in the balancing market. Before the balancing market, the Virtual Microgrid Association calls for its prosumers' flexibility and motivates them for smart load rescheduling to reduce exposure to market losses. Active and passive scheduling strategies are evaluated and a new hybrid approach is shown to achieve better profits for all values of the spread and the flexibility factor. We present a method of quantifying the value of a prosumer's flexibility and provide insights for a future policy of effectively compensating prosumers for their flexibility. The effects the penalty policy and the choice of the spread parameter have on the prosumers' behavior are studied and important insights are provided. The possibility of cooperation among prosumers in a certain geographical area is also studied, showing that it can lead to more intelligent and profitable operation.

1. Introduction

Until the 1980s, electricity systems were considered natural monopolies and were organized under cost-of-service regulation. Regulation in the EU and other countries promotes, or even dictates, that a certain percentage of the produced energy comes from Renewable Energy Sources (RES), thus creating a demand for RES energy as a diversified product. The major directions favored by the EU are the increase of RES penetration in the energy network and the liberalization of the energy market (directive 200/72/EC [1]). Thus, Energy Market Operators (MO) are forced to incorporate RES from small producers in their markets. As RES are being developed and used ever more extensively, a large degree of volatility and unpredictability is added to the grid, necessitating a radical revision of the traditional Grid and of the Market Model. Volatility constitutes a negative externality caused by certain (especially RES) market participants but affecting all participants, and in order to minimize it, the ones causing it should be appropriately penalized. Holding those who cause market volatility financially responsible for it, is increasingly important as the penetration of RES producers increases. With current market rules, RES producers or big consumers with high volatility get a free ride, and the rest of the market pays the price for it.

Distributed generation of electricity has been the principal trigger for developing the concept of the Smart Grid. Currently, RES are less (economically) competitive than traditional fossil fuel sources, while also causing extra costs to the system [2], partly due to their unpredictability, making it very challenging to satisfy demands for both cleaner and cheaper energy. This challenge has

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opened up new domains of research, including the development of new business models to facilitate the incorporation of more RES in the grid [3], by internalizing both positive (e.g. environmental and location benefits) bit also negative (e.g. volatility) externalities. As a result of the changes in the Electricity Market, medium and small energy prosumers (i.e. producers and consumers at the same time) are emerging at the center of interest in the new liberalized energy market. Extensive recent and ongoing research focuses on Demand Response (DR) techniques [4] as well as on integrating DR in the economic and optimization models [5]. A great deal of work also focuses on managing distributed RES in local electricity markets [6–9].

The new business and market models need effective information exchange in a distributed context, thus creating new challenges for the Information and Communication Technologies (ICT) field [10]. As ICT is introduced in the energy network, the concept of virtualization of energy resources also becomes feasible. A big energy prosumer is no longer necessarily formed through heavy investing on big prosumption facilities. Multiple small prosumers can organize themselves in bigger associations that participate as a single entity in the market, thus forming a virtual big energy prosumer, called a Virtual MicroGrid Association (VMGA) [11,12]. The VMGAs increase the market negotiation power of small prosumers, their combined reliability (and thus their ability to make Service Level Agreements — SLAs) and also decrease complexity and bookkeeping for the DSO who needs to deal with a smaller set of players. VMGs form the central idea in the ongoing Virtual MicroGrids for Smart Energy Networks (VIMSEN) project [13], the architecture of which is assumed in our present work. In compliance with the VIMSEN architecture, the prosumers will be called VIMSEN Prosumers (VPs). The concepts described above, open up new possibilities in the way electricity is traded. Small market participants become more active through the VIMSEN platform, and are represented by a new actor, the VMG Association. A VMG Association has similarities but also differences from traditional Virtual Power Plants (VPP) and Flexibility Aggregators, as explained in the following section. Thus, electricity trading/delivery cease to be strictly bounded to big beneficiaries. As a result, the electricity market is in need of new policies to embrace the emerging functionalities, address volatility issues and satisfy the new demands.

In the present work, we assume that the VIMSEN architecture, described in Section 3.1, is used as the marketplace for electricity trading. In this market setting, the MO makes Service Level Agreements (SLA) for the delivery of a certain amount of production or a certain amount of flexibility (consumption reduction) at specific time intervals with VMG Associations, which in turn make SLAs with their constituent individual VPs. Volatile/unpredictable prosumers (or VMG Associations of prosumers) are defined as those that make an SLA with a VMG Association (or with the MO, respectively) but cannot keep it and are forced to violate it. Volatility causes significant costs to market participants, which should be shouldered by those creating it, both for the sake of fairness but also in order to (have incentives) to minimize it. In Section 3.2 we introduce electricity market procedures based on a spread between buy and sell price in a BRP market, that can be used to penalize volatile participants, including prosumers and VMG Associations of prosumers. This proposed spread-based policy is general and can either be used by the MO to penalize the volatility/undpredictability/SLA non-conformance exhibited by VMG Associations in order to make them behave more responsibly, or be used by a VMG Association in order to make its constituent members do so (or be used in both situations). In the former case, it is a market policy (and may be subject to regulation) used in MO-to-VMG interactions, while in the latter case it is an internal policy of the VMG Association used in VMG-to-VP interactions. For the sake of being specific, we assume in our description the latter case, where the policy is used to penalize SLA violations between a VMGA and its constituent VPs. Starting with Section 4.1, we take the perspective of the VP. We analyze and compare two different strategies (an Active and a Passive one)), first introduced in [14], for strategic load rescheduling and give the conditions under which each strategy should be used. We also propose a novel, hybrid strategy that combines the benefits of the two approaches and show that it always achieves better profits than Active and Passive. We study the penalty savings obtained by a VP who uses the optimal rescheduling strategy as a function of the proposed per-unit penalty and the VP's flexibility. We also give insights on the effects that the size of the penalty has and the way it can be employed by the VMGA (or the MO) in motivating VPs (or VMG Associations, respectively) to function more or less conservatively, according to the VMG's (or the System Operator's)needs, thus providing important insights regarding the parameters of future pricing policies.

We also study the value of the VPs' flexibility, by quantifying the payback for being flexible and the degree to which it is worth investing in storage facilities or sacrificing the user's comfort in DR operations. The insights obtained can be used as input in storage sizing studies [15] and training algorithms that try to achieve a tradeoff between user's comfort and user's financial savings. They also help in describing a step-by-step procedure for defining the VP's flexibility based on the user's desires, which can be used as a reference point for developing future policies for exploiting and compensating a prosumer's flexibility.

In Section 4.2, we take the perspective of the VMGA by studying the value of cooperation between VPs belonging to the same VMG Association. We assess the concept of correlation between the production patterns of the cooperating VPs and study the revenues that the VPs enjoy from their cooperation as a function of the number of the VPs in a coalition and also as a function of their correlation. We show that the revenues gained by a VP are increased through cooperation with others, especially when the cooperating VPs have negatively-correlated forecasting errors. A somewhat surprising result is that there is value in the cooperation even for positively-correlated VPs. The results imply that a production investment is more profitable with respect to flexibility compensations when placed close to negatively correlated prosumers. Future investment subsidy policies can take these insights into account in order to motivate small production units to be developed in areas, where they would be more efficient. In Section 5, we present the simulation model and the data used, which is then employed in Section 6, to present performance evaluation results and comparisons between different strategies and cooperation cases. Specifically, we obtain results on the effect different parameters have on appropriately defined Value of Strategy, Value of Flexibility and Value of Cooperation metrics. Finally, in Section 7, we present our conclusions and the policy implications derived from our study.

2. Background and literature review

A typical wholesale electricity market in European countries is further divided in derivatives markets depending on the time of the trade as presented in Fig. 1 [16].

While single VPs are quite small market players, VMGAs can actually have the critical size required to participate in the wholesale electricity market. The market participation, decisions and general management of the associated VPs is materialized by through the VMG Association they belong to. The Association deals with the efficient integration of variable RES production and consumption loads' flexibility in the market, which is accomplished via sophisticated management of the resources with the use of ICT tools and algorithms [17]. Multiple RES production sites can also

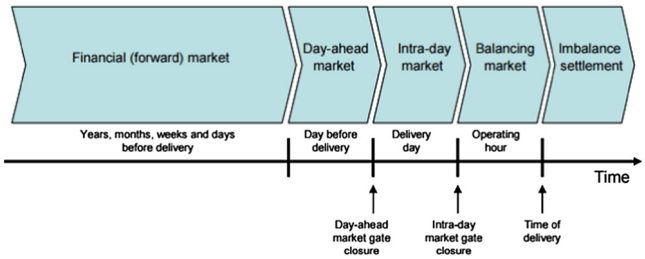

Fig. 1. Wholesale electricity markets [16].

jointly participate in the market through the concept of a Virtual Power Plant (VPP) [18], while consumers with DR flexibility can participate in the market through the concept of Aggregators [19]. The differences between the VPP, the Flexibility Aggregator, and the VMG Association concept proposed in the present paper are described in [20] & [21], and are summarized in the following. A VMG aggregating producers resembles a Virtual Power Plant (VPP), except that the former consists of a *dynamic* group of producers chosen so as to optimize different criteria at a time. A VMG combining consumers resembles a Flexibility Aggregators, with the important difference that a VMG is *not necessarily a profit seeking* market entity as a Flexibility Aggregator is. The VMG 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 customers and retailers. For example, a VMG's profit does *not* depend on the difference between the price offered to the market and that obtained from its constituent prosumers (in which case it would seek to minimize the latter, acting against them) but on (for example) the contracts made, that is, the number of registered prosumers in the VMG platform. This means a VMG Association's benefits can be *perfectly aligned* with those of its constituent prosumers, which is not the case with the usual concept of Flexibility Aggregators or of VPPs who are profit-seeking entities, with their own interests and strategies. It should be noted that the research problem studied in this paper covers all types of aggregators that currently exist in the electricity markets.

Forward trading opens up new possibilities for the market players, offering advantages for both suppliers and consumers. An analysis of the effects of the strategic use of forward trading in electricity markets is presented in [22]. A day-ahead market takes place one day before delivery. By taking into account the forecasts for the next day, different parties can trade their expected demand or supply, and subsequently the Market Operator (MO) is able to make a more informed scheduling for the next day when trying to match supply with demand.

Accurate forecasts of the VMGA's prosumption form an important asset for the Association to be able to efficiently bid in the day-ahead market. The MO runs all the supply and demand bids through a clearing process, which ultimately defines the electricity price, in order to match supply with demand. A review of forecasting models for electricity prices is presented in [23]. Put simply, the price is set where the (expected) curves for sell and buy quantities meet each other [24]. A state of the art market clearing model applied in the Power Matching City project is described in [14]. Based on the output of the process, the Association forms the Service Level Agreement (SLA) with the MO, for the next day, specifying how much energy it will produce/consume at each hour of the following day. The grouping of VPs in the VMGA affects the forecasting accuracy, as analyzed in [25]. Since both RES production (mainly) and the users' electricity consumption are subject to abrupt, real-time changes, presumption deviations from the SLA will always occur. These deviations cause undesired volatility and should be subject to financial penalties that can be imposed in various ways [26,27]. The users can attempt to avoid these charges by rescheduling their prosumption profile using unit commitment techniques, such as DR, making use of the prosumers' DR flexibility [28]. Numerous works, including [29–35] have provided optimal solutions to VP scheduling. However, the above studies assume either day-ahead scheduling or real-time scheduling without formerly-agreed SLAs and do not consider compensating for the deviations between a day-ahead SLA and a deviated profile.

Cooperation among prosumers of the same geographical area has been considered in order to tackle a variety of issues, such as power losses' minimization [36] and market profits maximization [37]. The role of the correlation factor among the prosumption patterns of the cooperating prosumers has been investigated in [38]. Other studies adopt data-driven approaches, where the cluster of prosumers optimize their bid to the wholesale market and a bi-level optimization problem is formed but without treating the price as a control variable [39]. In the work presented in [40], different scenarios for DR integration were compared in terms of profit maximization. "Scenario A" of [40] represents an active approach, whereas "scenario C" represents a passive one.

In our study, we take on the case where there are deviations from the day-ahead agreed SLA, making the demand curves of the prosumers different and also the prices of the balancing market different from the day-ahead prices. We apply load rescheduling in order to reduce exposure to market losses resulting from the different prices and also from the spread that is introduced between buy and sell price. We assume to have forecast/prediction algorithms for energy prosumers' participation in balancing markets and the respective forecasts for the Balancing Market prices. The way those forecasts are derived, as well as their accuracy, is out of the scope of the current paper and it is extensively discussed in [41–43].

We adopt Active and Passive approaches [14] and evaluate them in the case described. A Hybrid strategy is also proposed and is proved to be optimal for any value of the spread parameter used to penalize SLA violations. Our main contributions lie in that we also consider (1) a spread between buy and sell price of electricity, (2) the prosumers correlation (in terms of profiles deviations) when aggregating them in a cluster. We study the effects of the two factors and argue that they should be taken into account when applying demand side management algorithms. Finally, (3) we propose a novel "hybrid" scheduling strategy for near-real-time participation in balancing markets.

3. Market participation framework

3.1. Architecture, basic VMG association role and responsibilities

The actors of a typical Smart Grid architecture and the connections among them, as adopted by the VIMSEN project as well as by other research projects, are illustrated in Fig. 2. The main interrelations/responsibilities in which the new actors are engaged are identified as follows:

- Each VP is associated with a specific VMGA under contract by an SLA. Sole VPs that are not part of a VMGA are not considered in our framework.
- The VMGA is responsible for the negotiations – on behalf of its own VPs – with other VMGAs and/or Balance Responsible Parties (BRPs), or the biddings to the energy market (technically, through a VIMSEN portal), in order to sell the surplus energy (aggregate energy from prosumers) to BRPs or on the energy market, or to buy energy from the same, while maximizing profits.
- The VMGA can strategically motivate its VPs to apply smart rescheduling in order to improve its market position.

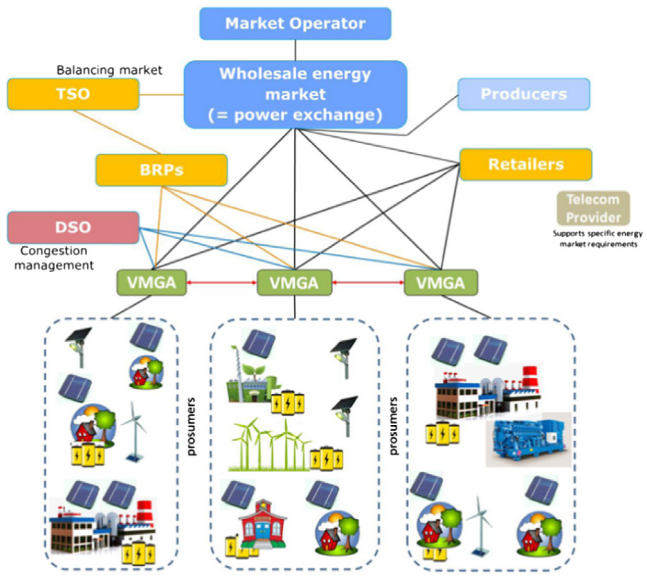

Fig. 2. VIMSEN Architecture [44].

- The Telecom Provider (TP) will be responsible for the reliable, on-time exchange of energy specific messages among VIMSEN actors.
- We assume that the trading above, satisfies any physical constraints, in the sense that the DSO makes sure that the energy can be bought/sold by the actors involved at their specific locations.
- We also assume that the VPs are price-takers, in the sense that they are part of a much bigger system and their own deviations are not directly reflected in the balancing market prices.

3.2. Market procedures and penalty policy

3.2.1. Day-ahead market

Producers and retailers make their bids (bidding curves) according to their forecasts for the next day. Based on these bids, the MO matches supply with demand and creates a set of hourly prices for the day-ahead market. These are extracted using market clearing techniques (commonly a bidding process with bidding curves) as is already applied from many market operating parties worldwide. The result of market clearing is that the price is higher for peak demand hours and lower for low demand hours. Wholesale suppliers and consumers (or, more generally, sellers and buyers) make contracts to buy/sell electricity for the next day, for a certain control area (that is the VMGA's portfolio). Considering hourly time blocks, the contract defines the quantity of electricity to be bought/sold at each hour of each day at a specific price, which is generally different for each hour. According to its portfolio's forecasted daily electricity needs, the VMGA can adjust its bids to better serve its clients and its own interests. After the day-ahead market gate closure, the SLA is formed. The SLA for a certain day is in the form of a curve representing agreed energy prosumption versus time.

3.2.2. Balancing market

According to its real-time needs, a VP might need more/less energy than that agreed in the SLA. These SLA violations are the quantities to be traded in the balancing market. The usual procedure is that it participates in the balancing market through bidding. Upon delivery, further deviations that occur, are compensated from the System Operator and charged a-posteriori to the VP (see Imbalance Settlement of Fig. 1) directly from the MO or via the BRP, depending on the architecture (it differs in some countries). Also, concerning the Balancing Market, the VMGA can undertake the role of the BRP for its own portfolio, or provide services to the corresponding BRP. Within the scope of our present work, we are only interested in the prices at which the VMGA and the VP buys and sells electricity in the Balancing Market, so our study applies to either of the above mentioned use cases.

The prices of the balancing market also differ from one hour to another. Compensating the VPs' imbalances from their SLAs bears additional costs, such as unexpected lines' congestion, need for reserves and need for fast-response, low-efficiency units (e.g. fuel-based) to be utilized. For this reason, it is justified to penalize the VPs who deviate from their SLA. In our model, instead of a fixed penalty, we propose that the penalty is incorporated in the balancing market prices. So, the VP that needs more energy than its SLA has to buy it at a higher per-unit price (balancing market price plus penalty) and a VP which needs to sell more energy, sells it in a lower price (balancing market price minus penalty). This means that there is a *spread* between the price that the VP receives for selling and the price that the VP pays for buying. So, if the market price for a certain hour of the balancing market is p, the VP receives two prices:

- (p + spread) for selling electricity
- (p – spread) for buying electricity

The concept of spread is thought to be used on top of existing balancing markets by applying the spread to the balancing prices.

The effect of the spread on the price of a certain hour is presented in Fig. 3, where the blue line represents the day-ahead market prices and the red line represents the balancing market prices.

Note that now in the balancing market, the VP receives generally less beneficial prices than in the day-ahead market because of the spread. The choice of the spread parameter is discussed later in this work, but it should be pointed out that it is also subject to regulation. In this paper, we only study the effect of the spread in the scheduling strategies. A spread policy can be used to penalize violations either in the SLA between a VMG and its constituent VPs, or between the MO and the VMG Associations (in each case, combined with any other penalty policy for the other case of violation), or it can be used as a unified policy in both situations.

Within the framework described, the VP can apply scheduling strategies (like load shifting) that reduce its exposure to violations. By applying the above, a procedure for defining each VP's flexibility and applying the scheduling is described:

(1) VMGA receives forecasts for the day-ahead from VPs and communicates bids to the MO.
(2) MO defines the day-ahead market prices and clears the day-ahead market. The SLAs are formed.
(3) After the day-ahead market gate closure and before the time of delivery, more accurate forecasts show the violations to be expected.
(4) The forecasts of the market-clearing prices (balancing market-prices before applying the spread) are created.
(5) VMGA decides the spread value depending on statistical data of flexibility and on its own goals (see Theorem 1 of the mathematical model).
(6) Based on (4) and (5), VMGA extracts the function for the value of flexibility, which is the cost for a VP subject to the flexibility it is willing to offer.

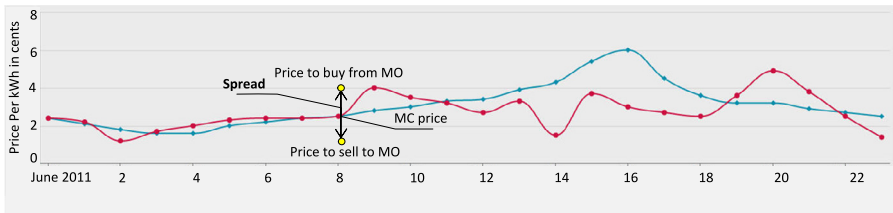

Fig. 3. Prices after apply of spread. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

(7) The curve is communicated to each VP and the VP chooses its flexibility according to the user's desires (e.g. if the curve's slope is high, user might be willing to sacrifice comfort for revenue).
(8) The scheduling algorithms for the VP are applied, subject to the flexibility value chosen and extract the load shifts to be made.
(9) Any deviations left are cleared in the balancing market.

Later, we provide specific insights on the way the spread of step 5 is defined and also the function of step 7 is derived.

4. Methodology and problem formulation

Considering a scheduling horizon h(e.g., $h = 24$ h), let us denote the VP's prosumption forecast (from the previous day) as an array of 24 elements, each representing the prosumption forecast for a given time unit (e.g hour) of the day ahead:

$$X = \left(X^1, X^2, \ldots, X^h\right)$$

where X^i expresses the energy that the VP consumes minus the energy it produces in hour i. The variable X^i is expressed in kWhs and can also be negative when the VP produces more energy than it consumes. The actual per hour prosumption (which is generally different from X) is denoted as

$$Y = \left(Y^1, Y^2, \ldots, Y^h\right)$$

and the difference between the two is the violations array (i.e. VP's SLA violations)

$$V = Y - X = \left(X^1 - Y^1, X^2 - Y^2, \ldots, X^h - Y^h\right),$$

where in the preceding vector subtraction is interpreted componentwise. An entry V^i can be negative if the VP consumes less energy or produces more energy than expected during hour i.

At time close to delivery time, the MO takes into account updated, more accurate, forecasts that become available, and broadcasts to the VMGAs the expected pricing curve for the balancing market (red curve of Fig. 3). Mathematically, this would be expressed as a h-element array

$$P = \left(P^1, P^2, \ldots, P^h\right),$$

where P^i denotes the market price (€ per kWh) at each of the h time intervals (hours). Vector P is extracted by market-clearing processes, according to the aggregated violations. Note that we refer to the balancing market prices. The day-ahead market prices do not concern our study, since we only focus on the trading after the day-ahead market gate closure. The more accurate the forecasts, the more similar P would be to the day-ahead market prices. To embed the implementation of penalties in the prices, a spread factor s is applied to P, as explained in the previous section (adding s to the prices for quantities that are bought and subtracting s from the prices for quantities that are sold) thus creating the Balancing Market Prices (M) as denoted in Eq. (1). Again, by M, we refer to the expected prices for the balancing market, which may differ from the final ones, if further deviations occur:

$$M = \left(M^1, M^2, \ldots, M^{24}\right)$$
$$\text{where } M^i = \begin{cases} P^i + s, V^i > 0 \\ P^i - s, V^i < 0, \end{cases} \tag{1}$$

Instead of waiting for the imbalance to happen, the VMGA can turn to its own portfolio VPs and give incentives for load rescheduling, in the form of load shifting or storage in batteries, in order to compensate for the violations before they occur.

4.1. Load scheduling at the VP layer

The goal of load scheduling is to form a more beneficial prosumption curve $\tilde{Y}$ and consequently violation curve $\tilde{V}$ than the ones expected (i.e., Y and V, respectively), so at to avoid costly transactions in the Balancing Market. Note that the physical network constraints are not implemented in this study; thus, the output should be evaluated by the System Operator before applied.

4.1.1. Active & passive strategies and the spread

The resulting curve can be made to more beneficial using two different Strategies, similarly to those described in [14].

• *Passive Strategy*: Tries to minimize its SLA violations at all times I, which we symbolically denote as

$$\tilde{V}^i \to 0, \text{ for all } i \text{ in } [1, h]$$

Thus, the passive strategy tries to move loads/production from hours with demand/supply surplus to hours with supply/demand surplus in order to minimize SLA violation (recall that a violation needs to be traded in the balancing market, in a generally non-beneficial price due to the spread). This strategy is referred to as passive, when the VP tries to meet its SLA.

• *Active Strategy*: The VP tries to counteract the overall system's imbalance. Given the application of market clearing processes by MO, a high price for a certain hour means that in this hour, there is extra demand for electricity. This Strategy tries to help the system to counteract its deviations from the aggregated SLAs (and benefit from that) by moving loads/production from the high/low price hours to the low/high ones.

$$\min\left\{\tilde{V}^i\right\} \text{ for } i \text{ where } P^i = high$$

$$\max\left\{\tilde{V}^i\right\} \text{ for } i \text{ where } P^i = low$$

where the terms high and low are defined by corresponding threshold values that are under our proposed system's control. Note that in the Active Strategy, the scheduling is planned regardless of the VP's own imbalance. Furthermore, let us consider a case where for a certain hour, the VP's SLA violation is opposite to the overall system's imbalance (e.g., has less demand than agreed in the SLA, while the overall system has extra demand than expected). In this case the VP makes profit from his SLA violation, because being opposite to the system's overall imbalance, this violation

actually helps the system. This strategy is referred to as active, when the VP tries to counteract the overall system's imbalance, without caring for its own SLA. In a nutshell, the passive strategy's objective is to minimize SLA violations whereas the active strategy's objective is to provoke SLA violations, opposite to the system's imbalance.

The degree of freedom for the VP's load shifting is constrained by the VPs' flexibility. For example, it is not acceptable for a VP's lights to be turned off at night and compensate for this by turning them on during daytime, so it is not a flexible load. However, a washing machine, or a PHEV can provide more flexibility. A VP's flexibility is expressed as a percentage f of flexible loads, such that the VP's prosumption Y^i at hour i (after applying load rescheduling for the flexible loads) becomes $\tilde{Y}^i$:

$$(1-f)\cdot Y^i < \tilde{Y}^i < (1+f)\cdot Y^i$$

With the nomenclature cleared, we can express the original optimization problem as the minimization of the VP's 24 h cost for electricity defined as:

$$\min_{\tilde{Y}^i} VP_{\text{Cost}} = \sum_{i=1}^{24}\left[M^i\cdot\left(\tilde{Y}^i - X^i\right)\right] = M * \left(\tilde{Y} - X\right) \tag{2a}$$

$$\text{subject to} \sum_{i=1}^{24}\tilde{Y}^i = \sum_{i=1}^{24} Y^i \tag{2b}$$

$$(1-f)\cdot Y^i \le \tilde{Y}^i \le (1+f)\cdot Y^i, \tag{2c}$$

where $*$ denotes vector inner product. That is, by moving flexible loads among hours with different prices, the VP is trying to minimize the overall 24h cost. Eq. (2b) expresses the fact that we do not deal with load shedding, but only with load rescheduling, so that the overall VP's 24h prosumption in the scheduling horizon remains the same.

For spread $s > 0$, the Active Strategy is exposed to non-beneficial decisions (note that Strategies are performed based on vector P and not BMP). This is validated by the fact that s can cause the following effect: Given a case where we have $P^i > P^j$ for a pair of hours i and j, the Active Strategy would make a load shift from i to j. But s can be high enough to cause $BMP^i < BMP^j$, thus rendering the load shift non-beneficial. The higher the value of s, the larger the number of pairs i, j for which this may be true, and the higher the cost of the Active Strategy.

With respect to problem (2) we state the following lemma:

Lemma 1. *Active Strategy is optimal when spread $s = 0$.*

Proof. Let us consider a VP with a violations array V and assume that after applying load rescheduling with Active Strategy the violations array becomes $\tilde{V}$. The proof will be done by contradiction. Let us suppose that there is a strategy Z with a violations array $\tilde{Z}$, different from $\tilde{V}$ that achieves lower cost. Since $s = 0$, we have $M^i = P^i$ for every i. Then from Eq. (2a), we have, regarding the costs of the Strategies, that

$$\sum_{i=1}^{24}\left[P^i\cdot\tilde{Z}^i\right] < \sum_{i=1}^{24}\left[P^i\cdot\tilde{V}^i\right] \text{ or } P*\tilde{Z} < P*\tilde{V}$$

where $*$ denotes vector inner product. This implies that there is at least one pair of hours a, b for which

$$P^a\cdot\tilde{Z}^a + P^b\cdot\tilde{Z}^b < P^a\cdot\tilde{V}^a + P^b\cdot\tilde{V}^b \tag{3a}$$

$$\text{with } \tilde{Z}^i = \tilde{V}^i \text{ for every } i \neq a, b. \tag{3b}$$

From (3a) we have

$$P^a\cdot\left(\tilde{Z}^a - \tilde{V}^a\right) + P^b\cdot\left(\tilde{Z}^b - \tilde{V}^b\right) < 0, \tag{3c}$$

and from (2b) and (3b) we get

$$\tilde{Z}^a = -\tilde{Z}^b \text{ and } \tilde{V}^a = -\tilde{V}^b. \tag{3d}$$

From (3c) and (3d), we have

$$P^a\cdot\left(\tilde{Z}^a - \tilde{V}^a\right) - P^b\cdot\left(\tilde{Z}^a - \tilde{V}^a\right) < 0,$$

$$\text{thus} \quad \left(\tilde{Z}^a - \tilde{V}^a\right)\cdot\left(P^a - P^b\right) < 0,$$

which yields two cases:

(1) if $P^a > P^b$, we have $\tilde{Z}^a < \tilde{V}^a$ and $\tilde{Z}^b > \tilde{V}^b$
(2) if $P^a < P^b$, we have $\tilde{Z}^a > \tilde{V}^a$ and $\tilde{Z}^b < \tilde{V}^b$

But from the definition of the Active Strategy, in each case Active would transfer as much load as possible:

(1) from $\tilde{V}^a$ to $\tilde{V}^b$, i.e. $\min\left\{\tilde{V}^a\right\}$ and $\max\left\{\tilde{V}^b\right\}$
(2) from $\tilde{V}^b$ to $\tilde{V}^a$, i.e. $\min\left\{\tilde{V}^b\right\}$ and $\max\left\{\tilde{V}^a\right\}$

From (2c), we have that both $\tilde{V}^i$ and $\tilde{Z}^i$ are bounded by the same margins. So for both cases we have

$$\tilde{V}^a = \tilde{Z}^a \quad \text{and} \quad \tilde{V}^b = \tilde{Z}^b \tag{3e}$$

From (3e) and (3b), we have that $\tilde{Z}^i = \tilde{V}^i$ for every i, i.e. $\tilde{Z} = \tilde{V}$

This means that Optimal Strategy and Active Strategy are identical, proving the lemma. □

The optimality of the Active Strategy when $s = 0$, implies the following corollary to Lemma 1:

Corollary 1. *For $s = 0$, Active Strategy has lower cost than Passive.*

As for the Passive Strategy, we can show the following lemma.

Lemma 2. *Passive Strategy is optimal when spread s is very high.*

Proof. Let us consider a VP with a violations array V and assume that after applying load rescheduling with Passive Strategy its violations array becomes $\tilde{V}$. The proof that Passive Strategy is optimal for high enough s will be done by contradiction. Let us assume that there is another strategy Z that when applied results in a violations array $\tilde{Z}$, different than $\tilde{V}$, and with lower cost. A very high s means that for every i, j with $\tilde{V}^i > 0$ and $\tilde{V}^j < 0$, we have that $M^i > M^j$. As in (3a), in this case there is at least one pair of hours a, b for which

$$M^a\cdot\tilde{Z}^a + M^b\cdot\tilde{Z}^b < P^a\cdot\tilde{V}^a + P^b\cdot\tilde{V}^b$$

which in view of Eqs. (1) and (3d) (that stands also here) becomes

$$\left(P^a + s\right)\cdot\tilde{Z}^a - \left(P^a - s\right)\cdot\tilde{Z}^a < \left(P^a + s\right)\cdot\tilde{V}^a - \left(P^a - s\right)\cdot\tilde{V}^a$$

Consequently, $\tilde{Z}^a\cdot(2s) < \tilde{V}^a\cdot 2s$, or $\tilde{Z}^a < \tilde{V}^a$. Then, because of (3b), we have $\tilde{Z} < \tilde{V}$, which implies that Z is the Passive Strategy since by definition it is the one that minimizes the violations and the violations array. □

Corollary 2 (*To Lemma 2*)**.** *When the spread s is high, Passive Strategy has lower cost than Active.*

Combining Eq. (1) with the VP's cost function given by (2a), we observe that the *VP_Cost* function is strictly increasing with respect to s for any $\tilde{Y}$, with the cost curve's slope given by

$$dVP\_Cost(s)/ds = l = \sum_{i=1}^{h}\left(\tilde{Y}^i - X^i\right).$$

Since Passive Strategy attempts to drive $\tilde{Y}^i - X^i$ as close to zero as possible, we have for the derivatives of the *VP_Cost* functions

$$l_{Active} > l_{Passive}. \tag{4}$$

From (4) and Lemmas 1 & 2 we conclude the following theorem.

Theorem 1. *Given the set S of spreads,there is unique $s^* \epsilon S$ for which Active and Passive Strategies' cost is equal.*

The preceding Theorem tells us that the VMG Association, when dealing with its constituent VPs, can strategically choose a general s value, in a way that can serve its goals. That is, it can choose a high spread s when it has reasons to want the VPs to try to meet their SLAs (function more "passively") or a low spread s when it wants to give incentives to the VPs to try to counteract the overall system's imbalance (function more "actively"). Thus, the VMGA can utilize s as a control variable for implementing the tradeoff between motivating users towards predictability (passive) or towards flexibility to rescheduling (active).

4.1.2. The proposed hybrid strategy

In this section, we propose a Hybrid Strategy as a way to combine the advantages of Active and Passive Strategies. Hybrid Strategy splits problem (2) in two subproblems, by dividing the set of hours into two groups:

∼ Group A contains all hour indices i for which there exists an hour z such that either of the following inequalities holds

$$P^i - s > P^z + s \quad \text{or} \tag{5a}$$

$$P^i + s < P^z - s. \tag{5b}$$

∼ Group B, contains all the remaining hours (in which the price difference among them, is smaller than the spread). The Hybrid Strategy is defined as follows:

Definition of Hybrid Strategy: apply the Active Strategy in Group A, and the Passive Strategy in Group B.

The following theorem can be proven:

Theorem 2. *Hybrid Strategy is optimal for every value s of the spread*

Proof. We denote the violations array resulting by the Hybrid strategy as $\tilde{Y}$ and will prove it to be optimal for any value of s. For the sake of contradiction, let us assume that $\tilde{Y}$ is not optimal and there is an optimal solution $\tilde{W} \neq \tilde{Y}$. If $\tilde{W} \neq \tilde{Y}$ then there is at least one pair of hours i, j such that:

$$\tilde{W}^i - \tilde{Y}^i = e \tag{6a}$$

$$\tilde{W}^j - \tilde{Y}^j = -e, \quad \text{and} \tag{6b}$$

$$\tilde{W}^a = \tilde{Y}^a \text{ for every } a \neq i, j, \tag{6c}$$

where e is a prosumption quantity in kWhs.

We distinguish three cases:

(1) Case $i, j \epsilon A$:

Condition (5) actually implies that Hybrid is based on M and not on P, as it defines the groups by the hour's M^i. From the proof of Lemma 1, by adding the value of s (in other words, replacing P^i with M^i), it is easily concluded that $\tilde{W}^a = \tilde{Y}^a$ for every hour $a \epsilon A$. So Hybrid is optimal for Group A. From Eq. (6c) we have that $\tilde{W}^a = \tilde{Y}^a$ for every $a \epsilon B$, proving $\tilde{W} = \tilde{Y}$.

(2) Case $i, j \epsilon B$:

Conditions (5) & (3) are equivalent and so Lemma 2 applies as it is, and $\tilde{W}^a = \tilde{Y}^a$ for every $a \epsilon B$. Similarly to above, from Eq. (6c) we have that $\tilde{W}^a = \tilde{Y}^a$ for every $a \epsilon A$, proving $\tilde{W} = \tilde{Y}$.

(3) Case $i \epsilon A, j \epsilon B$:

From Eqs. (6a) & (6b) we have: $M^i > M^j$. But this is in direct contradiction with (5a) & (5a), because if such i, j exist they would both be in group A by definition (because they act as an alternative policy z for each other). Since i, j always belong to the same group, constraint (2b) can be split in two constraints:

$$\sum_{i \epsilon A} \tilde{W}^i = K$$

$$\sum_{j \epsilon B} \tilde{W}^j = L$$

$$\text{with } K + L = \sum_{i=1}^{24} Y^i,$$

where each constraint involves only variables from one of the subvectors $\tilde{Y}^{i \epsilon A}$ and $\tilde{Y}^{i \epsilon B}$. Thus, the problem becomes trivially parallelizable, which means that the decomposed problem (Hybrid approach) is equivalent to the original one, and also from cases 1 and 2 above, we have $\tilde{W} = \tilde{Y}$. □

Up till now, we have looked at the Balancing market in the presence of the spread parameter s, which is used to penalize VPs that do not meet their SLAs. We proved that the optimal strategies to be followed by a VP for small and large values of the spread are the Active and the Passive strategies, respectively, and then showed that Hybrid is the optimal strategy for any value of the spread. With Theorem 2 proven, we assume from now on that all VPs apply the Hybrid Strategy in all cases. In accordance with Lemmas 1 and 2, Hybrid strategy is expected to approach Active Strategy for $s \rightarrow 0$ and approach Passive Strategy as s increases. We will verify this in the simulation results. We can intuitively understand the previous conclusions, by recalling that a low value of s represents favoring users' flexibility, whereas a high value of s represents favoring users' predictability.

The strategies described for an individual VP, when trying to minimize the violations and the corresponding penalties in its SLA with a VMG Association, are also applicable to a VMG Association in order to reschedule the loads of its constituent VPs and minimize the Association's violations and penalties in its SLA with the MO. The only difference is that when the rescheduling is decided collectively, the results are better than when decided distributedly (each user for itself) due to statistical multiplexing, or else the additional degrees of freedom the VMG Association has by aggregating the flexibility of several VPs.

In the following subsection, we look at the *value of flexibility* and how it is increased by combining VPs into VMG Associations. We define the difference between the Independent and the Associations case as the *value of cooperation*. Flexibility Aggregators (as described in the literature) can utilize the same possibility; the difference is that Flexibility Aggregators would do it in order to make profits themselves, while VMG Associations do it to create savings for their users.

4.1.3. Study of flexibility

In any case, the profits stemming from a prosumer cluster portfolio's flexibility have to be shared among (in the case of VMG Associations) or with (in the case of Flexibility Aggregators) the VPs who provide this flexibility. The flexibility of a VP is defined by parameter f of Eq. (2c). Thus, what we refer to as *value of flexibility* is the revenues the Association can achieve by using the flexibility of its VPs. By using the knowledge of the flexibility value, the Association can introduce new ways of pricing its clients or even introduce a new energy market product, which can be called "Flexibility Retail Market", to buy flexibility from the VPs.

Assuming $s = s^*$, (i.e., the spread at which Active and Passive Strategies' cost is equal, we want to study the way the Cost of the VP changes with f. From problem (2) we have that the Cost of the VP is $\sum_{i=1}^{24} \left[M^i \cdot \tilde{V}^i \right] = M * \tilde{V}$, where $\tilde{V}^i = \tilde{Y}^i - X^i$ is the violation remaining after the optimal Hybrid strategy is applied. For the hours i in which the Active Strategy is applied, we have

$$\tilde{V}_A^i = V^i - f \cdot Y^i,$$

whereas for the hours i where the Passive Strategy is applied, we have

$$\tilde{V}_P^i = \begin{cases} V^i - f \cdot Y^i, & V^i > f \cdot Y^i \\ 0, & V^i < f \cdot Y^i. \end{cases}$$

This is because Passive stops adding or subtracting loads from hour i once $\tilde{V}^i = 0$ (i.e., once the violation at time i has been minimized), while Active continues subtracting load from hour i trying to reverse the violation, as long as more flexibility is available. So, when f increases $\tilde{V}_P^i$ also decreases (but not linearly) up to certain point where $\tilde{V}_P^i = 0$, beyond which it does not decrease anymore. So, although the function's derivatives cannot be expressed in closed analytical form (because $\tilde{V}_P^i$ is not differentiable at point $V^i = f \cdot Y^i$), it is quite clear that:

Statement 1: The cost of the VP is astrictly decreasing, non-linear and convex function *VP_Cost* (f) of f.

The validity of Statement 1 will also be confirmed through the simulation results of Section 6. By the non-linearity and convexity of the *VP_Cost* (f) function, one can see that sacrificing comfort to achieve very high values of flexibility is rewarded with diminishing returns, i.e, some revenue is obtained but not necessarily as high as the discomfort level caused. On the other hand, from Eq. (2a) we have that the *VP_Cost* (f) and consequently the value of flexibility is also dependent on the value of s.

4.2. VP cooperation and rescheduling at the VMG layer

In this section, we assess the advantages that can be obtained through the cooperation of multiple VPs that are aggregated in *coalitions*, or clusters, namely the VMG Associations. We also study the profits of cooperation in the case of positive, zero, and negative correlation among the violation patterns of the VPs forming a cluster, giving insights on the criteria that should be used to cluster VPs. In particular, we show that VPs whose violation patterns are negatively correlated can gain important benefits from their cooperation, but the benefits of cooperation also extend, even though reduced, to VPs that are uncorrelated or even positively correlated.

In the case of non-cooperative VPs, the VMGA communicates the balancing market pricing pattern to the VPs and the scheduling algorithms run in each VP. In the cooperative case, the VPs communicate to the VMGA their violations , the VMGA applies the cooperative scheduling algorithms (that now run in the Association's side) and the outputs are communicated back to the VPs.

Denoting the final violations array of a VP A and a VP B as $\tilde{V}_A$ and $\tilde{V}_B$, respectively, the total cost of the VPs' violations when acting individually (non-cooperatively) would be

$$Cost^{non-coop} = VP\_Cost_A + VP\_Cost_B = \sum_{i=1}^{h} M_A^i \cdot \tilde{V}_A^i + \sum_{i=1}^{h} M_B^i \cdot \tilde{V}_B^i$$

whereas the cost of the violations of a cluster made up of VP A and B (cooperating) would be

$$Cost^{coop} = VP\_Cost_{A \bigcup B} = \sum_{i=1}^{h} M_{AB}^i \cdot \left(\tilde{V}_A^i + \tilde{V}_B^i\right).$$

Note that $Cost^{coop}$ is not equivalent to $Cost^{non-coop}$, because for those hours i that $\tilde{V}_A^i \cdot \tilde{V}_B^i < 0$, we have $M_A^i \neq M_B^i$ (see Eq. (1)). In other words, when A and B combine in a cluster they may reduce or overhaul some of the SLA violations (penalized through the spread s).

For all hours i for which we have $\tilde{V}_A^i \cdot \tilde{V}_B^i > 0$, we have

$$Cost^{non-coop}(i) = Cost^{coop}(i), \quad for\ i\ s.t.\ \tilde{V}_A^i \cdot \tilde{V}_B^i > 0, \tag{7a}$$

Let us consider now an hour i where A and B have opposite violations, that is,

$$\tilde{V}_A^i \cdot \tilde{V}_B^i < 0. \tag{7b}$$

For the individual case we then have

$$\begin{aligned} M_A^i \cdot \tilde{V}_A^i + M_B^i \cdot \tilde{V}_B^i &= \left(P^i + s\right) \cdot \tilde{V}_A^i + \left(P^i - s\right) \cdot \tilde{V}_B^i \\ &= P^i \cdot \left(\tilde{V}_A^i + \tilde{V}_B^i\right) + s \cdot \left(\tilde{V}_A^i - \tilde{V}_B^i\right), \end{aligned} \tag{7c}$$

whereas for the cooperative case we have

$$\begin{aligned} M_{AB}^i \cdot \left(\tilde{V}_A^i + \tilde{V}_B^i\right) &= \left(P^i + s\right)\left(\tilde{V}_A^i + \tilde{V}_B^i\right) \\ &= P^i \cdot \left(\tilde{V}_A^i + \tilde{V}_B^i\right) + s \cdot \left(\tilde{V}_A^i + \tilde{V}_B^i\right). \end{aligned} \tag{7d}$$

From Eqs. (7c) & (7d) and (7b) we conclude that

$$M_A^i \cdot \tilde{V}_A^i + M_B^i \cdot \tilde{V}_B^i \geq M_{AB}^i \cdot \left(\tilde{V}_A^i + \tilde{V}_B^i\right) \tag{7e}$$

From (7e) & Eq. (7a), we have for the overall cost of the non-cooperative and the cooperative case:

$$\sum_{i=1}^{24}\left[M_A^i \cdot \tilde{V}_A^i\right] + \sum_{i=1}^{24}\left[M_B^i \cdot \tilde{V}_B^i\right] \geq \sum_{i=1}^{24}\left[M_{AB}^i \cdot \left(\tilde{V}_A^i + \tilde{V}_B^i\right)\right] \tag{7f}$$

Eq. (7f) expresses that the cost of two VPs' violations is higher than or equal to that of a virtual united VP (cluster) that participates in the market as one entity and thus there is a profit from their cooperation. An important parameter that affects the amount of this profit is the number of hours i for which (7b) stands. This is related to the criteria that are used to select the particular VPs that should be grouped together into clusters for energy exchange.

Useful in making the clustering decisions for VPs is the concept of *VPs' correlation*. A VP A will be said to be *positively correlated* to a VP B when their violations patterns are affected (by the weather and other conditions) probabilistically in the same way, or mathematically, if their violation vectors defined as $\tilde{V}_A$ and $\tilde{V}_B$, have strictly positive cross-correlation:

$$E(\tilde{V}_A * \tilde{V}_B) > 0,$$

where * denotes the inner product between vectors and $E()$ denotes the expected value. An example of positively correlated VPs would be a set of solar parks located in nearby geographical areas, where an unexpected loss of sunshine would affect all the VP production patterns in the same way. Similarly, VP A will be said to be negatively correlated to VP B when an increase/decrease in the production of A is connected with a corresponding decrease/increase in the production of B, that is,

$$E(\tilde{V}_A * \tilde{V}_B) < 0.$$

VP A will be said to be uncorrelated to VP B, when their production sources are independently affected, that is,

$$E(\tilde{V}_A * \tilde{V}_B) = E\left(\tilde{V}_A\right) * E\left(\tilde{V}_B\right) = 0,$$

where we have assumed that $E\left(\tilde{V}_A\right) = E\left(\tilde{V}_B\right) = 0$, as is the case for unbiased estimators (forecasters).

In the performance results to be described in Section 6, we examine the cases where a cluster is composed of: (a) maximally positively correlated VPs, (b) uncorrelated VPs and (c) pairs of negatively correlated VPs. Our results will show that the profit of cooperation is low but positive for positive correlated VPs, higher for uncorrelated VPs, and is the highest for negatively correlated VPs.

5. Model and data used for simulation

5.1. Simulation model

In our simulation experiments, a VP is modeled as a set of 4 parameters, $VP = (S, B, DF, f)$, where $S = \left(S^1, S^2, \ldots, S^{24}\right)$ is a 24-element array denoting the amounts of energy (kWhs) that the *VP* agrees to sell (in its SLA) throughout the next day with a sampling time of one hour. Also, $B = \left(B^1, B^2, \ldots, B^{24}\right)$ is a 24-element array denoting the amounts of energy (kWhs) that the *VP* agrees to buy (in its SLA) throughout the next day with a sampling time of one hour. For demonstration purposes, we chose a 24h scheduling horizon, in order to obtain the results throughout a whole day. It should be noted though, that balancing market prices are generally unpredictable and the larger the scheduling horizon the more the results will deviate from the actual optimal. Nevertheless this issue can be tackled by iteratively running the scheduling algorithm in real-time during the day. The implementation of the real-time version is left for a future study.

We define the prosumption array as $X = B - S$. We also define a violation vector V as the difference between the vector Y containing the actual hourly prosumption values and the vector X containing the forecasted prosumption pattern, that is, $V = \left(v^1, v^2, \ldots, v^{24}\right) = X - Y$. The entry v^i is assumed to be a random variable that is uniformly distributed in [−DF, DF]; parameter *DF* is referred to as the Deviation Factor, indicating the margins ($\pm DF$) according to which the *VP* is expected to deviate from the SLA, and is expressed in kWh per hour. The Flexibility Factor f is a float variable, indicating the amount of energy prosumption shifting that the VP can accomplish. It is expressed as a scalar between 0 and 1 or corresponding % value (0 corresponds to no flexibility, and 1 or 100% corresponds to all loads and/or supply units being flexible). Note that prosumption shifting can be accomplished either by shifting loads and/or by shifting energy supply (e.g. using scheduling for controllable units or storage capacity for RES).

The *VP* communicates its deviation vector V to the VMGA. At the Association level, a set of market-clearing prices is created for each hour of a certain day and is represented by vector:

$$P = \left(P^1, P^2, \ldots, P^{24}\right)$$

is a 24-element array denoting the market price (€ per kWh) at each of the 24 time intervals (hours) before the spread is applied. Taking into account the spread s (see Section 3.2), we obtain the Balancing Market Prices by Eq. (1) and assign them to vector M.

Vector M is communicated by the Association to the *VP*. By now, the *VP* can calculate the expected daily *Cost* with no scheduling techniques applied, to use it as a reference for the strategies evaluation:

$$VP\_Cost\ (\varnothing) = \sum_{i=1}^{24} \left[V^i \cdot M^i\right],$$

where the ∅ (null) in the parenthesis signifies the cost when no rescheduling strategy is applied. The *VP* applies load shifting strategy L in {Active, Passive, Hybrid}, subject to its flexibility factor f, thus changing its initial violation vector V to a new violation vector denoted as $V\ (L)$. The cost of the applied strategy is calculated as

$$VP\_Cost\ (L) = \sum_{i=1}^{24} \left[V(L)^i \cdot M^i\right],$$

for any strategy L in {Active, Passive, Hybrid}.

The percentage savings realized by strategy L is given as

$$\text{Value of Strategy } L\,(\text{VOS}\,(L))\ \% = (VP\_Cost\ (\varnothing) - VP\_Cost\ (L)) \cdot 100/VP\_Cost\ (\varnothing)\,.$$

our metric of merit for evaluating the performance of the strategy (Active, Passive, or Hybrid) applied.

5.2. VPs cooperation

A use case of cooperation was implemented for n VPs in direct representation of the mathematical model and the daily energy cost per VP was calculated resulting in two cases: the average daily cost per VP when they do not cooperate, denoted as $Cost^{non-coop}$, and the average daily cost per VP when they cooperate in a cluster, denoted as $Cost^{coop}$. For the calculation of $Cost^{coop}$, we formed and used the $24 \cdot n$ violations matrix V_n, with n being the number of cooperating VPs and elements $V_n^{a,i}$ representing the violation of VP a at hour i:

$$Cost^{non-coop} = \frac{\sum_{a=1}^{n} (VP\_Cost^a)}{n}$$

$$Cost^{coop} = \frac{\sum_{i=1}^{24} \left[\left(\sum_{a=1}^{n} V^{a,i}\right) \cdot M^i\right]}{n}$$

The difference between these values gives the daily monetary profit that each VP gains on average through cooperation and the corresponding % gain is defined as:

$$\text{Value of Cooperation (VOC) } \% = \left(Cost^{non-coop} - Cost^{coop}\right) \cdot 100/Cost^{non-coop}$$

5.3. Data used in simulations

The implementation was made in Python environment. For the pricing and the prosumption data, we used sets of values extracted from the VIMSEN Decision Support System (DSS) [45], which provides open source data for production, consumption and pricing derived from Hellenic Electricity Distribution Network Operator, regarding 100 RES producers (of different kinds), 150 consumers (industrial, commercial, residential) and 50 very small prosumers in Greece during 2015. Many of them are located in the same LV/MV substation, making it feasible to apply the proposed aggregation strategies. Because variable v^i of the violation vector V of the model is a random variable, the simulation was run for a large number of iterations to extract the average value for all the results.

5.3.1. Strategies evaluation and study of spread

As school buildings constitute an important prosumer type in Greece whose data is recorded in VIMSEN's DSS [45], for the prosumption data we consider a typical school at a typical day in Athens. For the results presented in Section 6.1 regarding the strategies' evaluation and the choice of spread, we assume *DF* =1.5 kW, $f = 25\%$ and an average presumption array

$$X = [1.54, 2.12, 2.05, 1.52, 1.42, 1.42, 1.47, 0.89, 0.87, 1.16, 0.76, 0.91, 0.72, 1.13, 3.51, 3.45, 3.74, 4.26, 4.37, 3.31, 1.58, 1.71, 1.73, 1.60]$$

The pricing data was also extracted from [45] and is given by the vector:

$$P = [3.75, 3.66, 3.66, 3.70, 3.66, 3.54, 3.70, 5.03, 6.27, 6.5, 7.43, 7.47, 7.21, 6.80, 6.41, 5.78, 6, 6, 5.5, 3.9, 2.9, 3.7, 3.95, 5.5.]$$

5.3.2. Set of prosumers, cooperation and correlation

For the results presented in Section 6.3 regarding the value of the cooperation among the VPs as well as the effect of their correlation, we used both real and simulated data. The real data was extracted from [45] for a set of different prosumers all for March 21st 2015, 24 h. For the simulated data experiments, 100

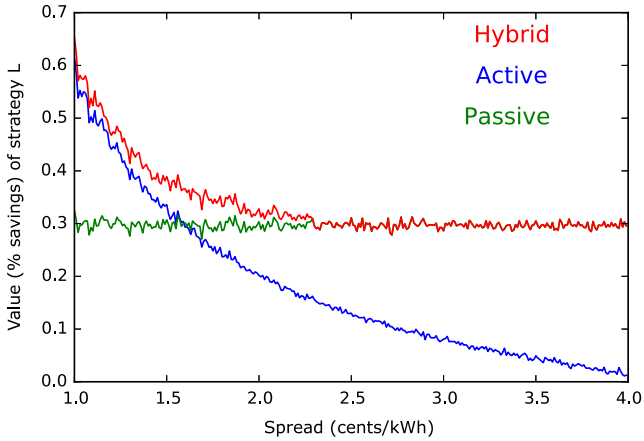

Fig. 4. Value (% savings) of Strategy L = Active, Passive, or Hybrid as a function of spread s.

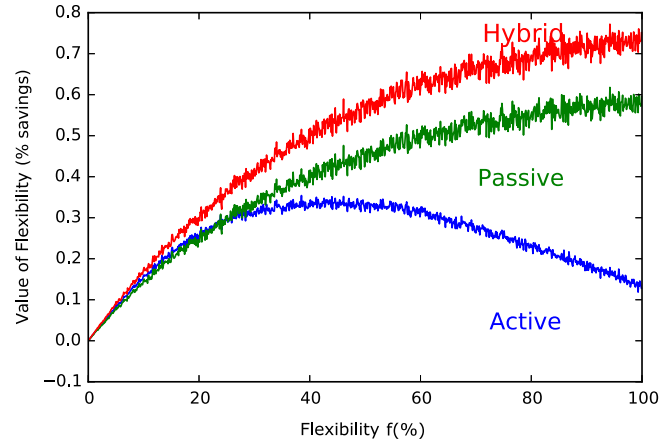

Fig. 5. Value of Flexibility (%savings) as a function of flexibility parameter f.

synthetic profiles were created by random uniform distributions of prosumption with a median value of 3 kWh and a standard deviation of 3. In both cases, we again assumed $f = 25\%$ and $DF = 1.5$.

6. Simulation results and discussion

In this section, we evaluate the strategies described in Section 4.1 and also the cooperation framework defined in Section 4.2. In particular, in Section 6.1, we evaluate the Value of Strategy for the Active, passive and Hybrid strategies, and study the effect of the spread parameter s. In Section 6.2, we analyze the Value of Flexibility of the VPs, as a function of parameter f. The savings that can be obtained through cooperation, that is the Value of Cooperation % metric, are investigated in Section 6.3 along with the role played by correlation factor.

6.1. Policies' evaluation and study of spread

Through simulation, we evaluate the Value of Strategy L (% savings) gained with each strategy L in {Active, Passive, or Hybrid} for different values of s. The results obtained are depicted in Fig. 4. We present the results beginning from s = 1, because in lower spreads the curves scale are higher and the results would not be as clear for the reader.

The results in Fig. 4 are in completely aligned with Lemmas 1 and 2, and Theorems 1 and 2 proved in Section 4.1, as follows:

- The performance of the Active strategy approaches that of the Hybrid strategy for small values of s, as expected by Lemma 1. Its Value of Strategy metric (% savings) is monotonically decreasing with s as expected, since a higher spread trims the price difference between a high-value and a low-value element of P.
- The value (% savings) of Passive strategy is not affected by the spread s, as expected, since by definition the Passive strategy tries to meet the *VP*'s SLA agreement, regardless of the s value. For a high spread, Passive strategy becomes optimal, as expected by Lemma 2
- After a certain spread value, the Active strategy becomes less beneficial than the Passive. There is a unique s value in which the two strategies are equally beneficial (Theorem 1).
- The lower the s, the more "actively" the Hybrid strategy behaves and the higher the s, the more "passively" the Hybrid strategy behaves.
- The Hybrid strategy (optimal for every s, from Theorem 2) outperforms the other two strategies examined, yielding significant savings ranging from 30%–60% for the parameter values examined.

6.2. The value of flexibility

The model used in the previous section to evaluate the rescheduling strategies, considered a single *VP* having a given flexibility factor f. In this subsection, we investigate the degree to which a VMG Association's profits are affected by its portfolio's flexibility. The simulation experiments assumed fixed spread equal to s^* and flexibility parameter f varying from 0 up to 100%. Fig. 5 depicts the Value of Flexibility (% savings) metric as a function of f. We observe that the Value of Flexibility (savings) function under the Hybrid strategy is indeed strictly increasing, not linear and concave, confirming Statement 1 of Section 4.1 . As expected, the Hybrid strategy achieves the best % savings over all strategies and for all values of f, reaching savings of about 75% for high flexibility, in the experiments conducted.

Note that the Active strategy becomes less profitable when more than 25% flexibility is available. This is because the simulation was run for $s = s^*$, with s^* extracted in the results of Section 6.1 for $f = 25\%$ (the intersection point in Fig. 4 gives $s^* = 1.6$). But what is more important at this point is that Hybrid strategy is verified to be the most profitable strategy for every value of f and for every value of s. So, from now on we assume that all *VPs* apply the Hybrid strategy in all cases.

Simulation experiments were carried out for a range of values of f (0–100%) and values of s (1–4 cents/kWh) and a 3D curve was extracted, showing the way the Value of Flexibility(VOF) metric depends on these two factors (Fig. 6). Such a curve is extracted by the Association after step 4 of the procedure described in Section 3.2 for defining each VP's flexibility. Thus, even in a use case where the value of s is not constant but is adapted by the MO, the Association can also adapt the value (savings) function of flexibility by applying the real-time s value to Fig. 6 and extract the respective 2D curve.

6.3. Evaluation of the value of cooperation

In this set of experiments, we evaluated the Value of Cooperation metric as a function of the number n of cooperating VPs under the negatively-, positively- and un-correlated VP cases using the equations of Section 4.2. For the simulation we used the same

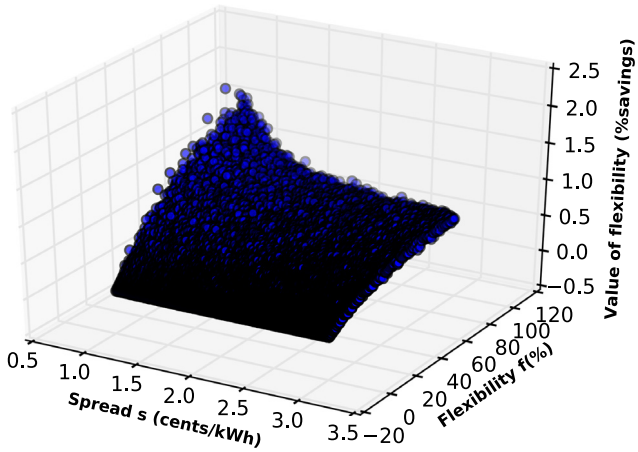

Fig. 6. Value of flexibility (% savings) as a function of the spread s and flexibility parameter f (Hybrid Strategy is applied).

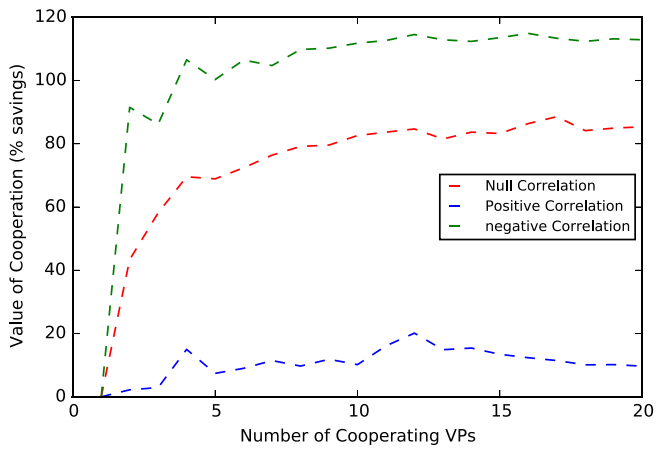

Fig. 7. Value of Cooperation (% savings) as a function of the number n of cooperating VPs.

profile and deviation distribution data with Sections 6.1 and 6.2. The results are plotted on the same graph in Fig. 7 for the three correlation cases, and for 1 to $n = 20$ cooperating VPs. The simulation algorithm aggregates the prosumers' profiles and applies the Hybrid strategy as described in Section 4.2.

Fig. 7 confirms Eq. (7f), stating that the savings due to cooperation over the non-cooperative case are always positive (even for positively-correlated VPs!). It also shows that negatively correlated VPs exhibit savings of the order of 100%, as expected, since they are able to cancel out each other's violations when cooperating. The Value of Cooperation is significantly smaller in the case of independent VPs (of the order of 40% when $n = 2$), but it increases rapidly with n, and approaches that of negatively-correlated VPs when n is large. Hence, a higher number of cooperating VPs results to a higher profit per VP when the VPs are independent. When the VPs are positively or negatively-correlated, the incorporation of a very large number of VPs in the cluster has diminishing returns, in the sense that it yields little savings beyond a certain point. Forming larger coalitions, however, is highly beneficial when the VPs are independent.

To demonstrate these conclusions more clearly, we run additional simulations for a set of synthetic (simulated as opposed to real) prosumption data and a larger number of cooperating VPs ($n = 100$). The results are shown in Fig. 8. We observe that the curve obtained with the real data is actually no different than that obtained with synthetic data.

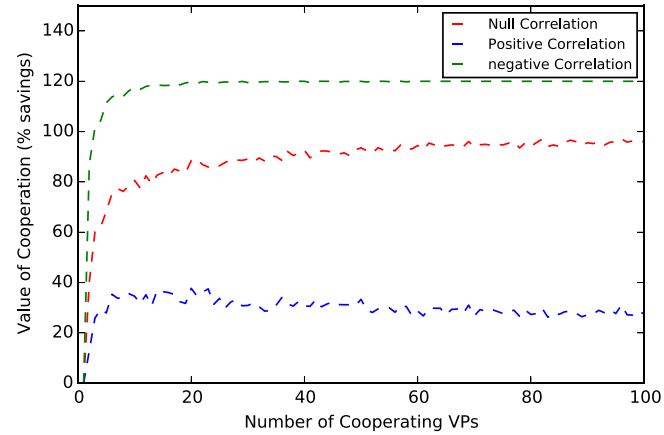

Fig. 8. Value of Cooperation (% savings) as a function of the number of cooperating VPs with simulated data.

7. Conclusions and policy implications

An energy market model (Day-ahead and balancing market) was described that is aligned with the emerging liberalized electricity market expected to prevail within the next years. Given the Day-ahead Market SLA agreements, we considered an approach where a market beneficiary violating its SLA is exposed to a dynamic per-unit penalty (the so called spread) through trading its SLA violations in the balancing market, instead of incurring a fixed SLA violation penalty. Three different strategies (Active and Passive and Hybrid) for load shifting towards reducing market losses were described, simulated and compared. The Active strategy was proven to outperform the Passive one for spread values below a specific point. A Hybrid strategy, combining the advantages of the two, was also proposed and shown both theoretically and experimentally to perform better for any value of the flexibility and the spread. The spread parameter can be strategically chosen by the MO to give incentives towards the desired energy prosumers' behavior. Our study can provide insights to policy makers for taking into account the expected prosumers' behavior when defining the penalty policy. Applying the Hybrid strategy, we extracted a curve of revenue improvements as a function of flexibility and observed that they are linked in a monotonically increasing and convex way. We also presented a 3D graph showing the improvements obtained for different values for the flexibility and the spread. Future research can use this study as an input: (i) for algorithms that define a user's flexibility versus discomfort tradeoff, modeling and accounting for the user's customized preferences, and (ii) policies regarding the consumers' compensation for providing flexibility. The benefits of cooperation were also demonstrated and studied for the case of multiple VPs forming clusters. The benefits of cooperation are higher when the cooperating VPs have negatively-correlated violation patterns (in which case SLA violations may be reduced by close to 100%) ,but they can also become significant for VPs with independent production patterns, by increasing the number of participating VPs. Our results can provide insights to investors and help subsidy policy makers in motivating investments of the most suitable kind in terms of DR flexibility efficiency in each geographical area. Future research directions include studying the degree to which cooperating VPs can increase their negotiating power towards becoming significant and active players in the energy market, by implementing a real-time iterative version of the scheduling algorithm to compensate for inaccurate forecasts, also taking into account physical network constraints. The work also opens other research questions; for example, would a VMG Association risk buying Flexibility at a fixed

price, hoping to be able to use it profitably in the wholesale market, or would it rather call for flexibility on-demand and share the profits with the VPs? An Association may also classify the VPs in its portfolio into categories according to their flexibility profile, with different contracts applying to different categories.

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