Micro grid scheduling policies, forecasting errors, and cooperation based on production correlation

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***Abstract*—We present scheduling policies that can be used by Micro Grids (MGs) with the possibility of energy production, consumption and storage, in the context of a novel Smart Grid architecture. Assuming a Day-Ahead market, we investigate the management of resources so as to achieve higher profit for the MGs under various operating scenarios. The possibility of cooperation among MGs in the presence of forecast errors is also studied, demonstrating that it can lead to more intelligent and profitable operation of the MG resources. The profits of cooperation among MGs whose production patterns have positive, zero, or negative correlation are assessed.**

Keywords—*Micro Grids, scheduling policy, Micro Grid cooperation, forecast deviation, resources virtual integration*

I. Introduction

Renewable energy sources (RES) play an increasingly important role in the energy market, with their integration in the future Smart Grid being the subject of much recent research [1]. Medium and small energy prosumers (producers and consumers at the same time) are important participants of a liberalized energy market. The formation of Micro Grid (MG) coalitions in order to enhance their market role [4],[5] also shows promising results. As the energy pricing model will no longer be based on a flat price, the times at which an MG buys or sells energy is important in optimizing its profit. In this context, energy storage management [7] is attracting new interest, given the important storage possibilities [6] offered by plug-in electric vehicles.

Regulation in many countries dictates that a certain percentage of the energy comes from RES, thus creating a demand for RES energy. The market for RES energy will probably be based on business models that are different than the feed-in tariff policies currently used in many countries. The major directions promoted by the EU are the increase of RES penetration and the liberalization of the energy market (directive 200/72/EC [12]). In a fully liberalized unsubsidized market, RES producers may find it hard to compete unless new business models are devised that will take into account the positive externalities of RES energy (namely green production and avoidance of CO2 emission penalties, and production sites close to consumers with corresponding reductions in the investments needed for the distribution network), and try to return these benefits to the small producers that create them. Since RES production is distributed, a decentralized market operation model is needed to help MGs have a more active role and participation in the energy market. Such a model creates new challenges for the Information and Communication Technologies (ICT) field [8]. As ICT is introduced in the energy grid, the virtualization of energy resources also becomes feasible, where a big energy prosumer is no longer necessarily formed by investing large capital on big prosumption facilities. Multiple small prosumers (MGs) can organize themselves in associations that participate as a single entity in the market, thus forming big energy prosumers, which we call Virtual Micro Grids (VMG). The traditional power production plant is expanded to the concept of the Virtual Power Plant, an entity that underpins the growing number of small production units [9], while the VMG will probably constitute a key actor that brings together RES producers in the new market models. Figure 1 displays the new approach, where MGs can pool energy resources together into VMGs that can be direct participants in a decentralized energy market. The VMG concept is a central idea in the ongoing Virtual Micro Grids for Smart Energy Networks (VIMSEN) project [13].

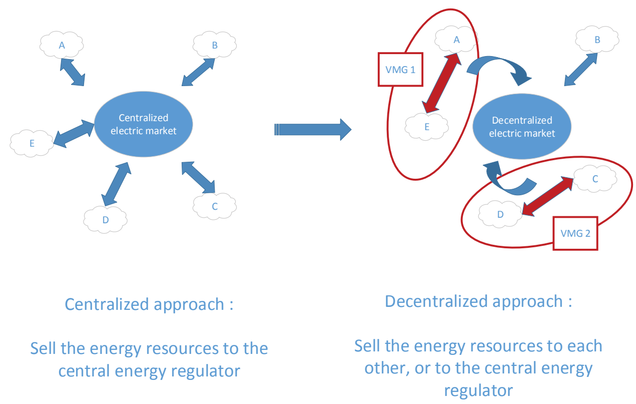

Fig. 1. VMGs and Decentralized Energy Market

The present paper focuses on the scheduling policies that can used by MGs participating in the energy market when making their sell/buy/store decisions, as well as the advantages that can be obtained through the cooperation of multiple MGs in bigger coalitions (the VMGs). We first look

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into the case of a single MG that is able to produce, consume and store energy, proposing and evaluating nine (9) scheduling policies that can be used to make its market (buy/sell/store) decisions. A Day-Ahead market is assumed and the costs/profits of an MG for the different resource management algorithms are evaluated, first by assuming that the actual daily prosumption pattern of the MG is the same as the forecasted one, and then by introducing a deviation vector to model inaccuracies in the forecasts. In the presence of forecast errors, the MG fails to meet its Service Level Agreement (SLA) and pays a penalty for this. The possibility of cooperation among Micro Grids is then studied, with the results demonstrating a more intelligent and profitable operation of the MG resources when they are pooled together. The main idea is that MG coalitions (VMGs), through mutual energy exchanges can help each other reduce the forecast error effects and the corresponding SLA deviations. The profits of cooperation are also studied in the case of positive, null and negative correlation among the production patterns of the cooperating MGs, giving insight on the criteria that should be used to cluster MGs into VMGs. We show that MGs whose production patterns are negatively correlated can gain important benefits from their cooperation, but the cooperation benefits also extend, even though reduced, to independent or even positively correlated MGs.

A) Contribution Points

The ways and the policies according to which MGs operate and make their decisions in order to benefit from this newly introduced framework are the subject of this paper. The main contribution points of the paper can be summarized as follows:

- A novel Smart Grid architecture is introduced, composing the framework in which the system model is developed.
- A variety of scheduling algorithms are proposed regarding the management of an MG's own resources in this particular model framework, in a single MG (non-interconnected with other MGs) scenario.
- A deviation vector is introduced, and the effect of forecast inaccuracies in the algorithms' performance is studied.
- A cooperative scenario is proposed, where the MGs are shown to gain profits by forming virtual MG cooperations (VMGs) and jointly making their buy/sell/store decisions.
- A correlation factor is introduced on the production profiles of the MGs forming a VMG, and the effect of the correlation among the cooperating MGs on the total profits is studied.

II. Model Used for the Pricing, Forecast and Storage Capabilities

A brief description of the system's architecture, being developed in the VIMSEN project, is depicted in Figure 2. The main actors in the system's architecture are:

- The Energy Market Operator, which may be a department of the Big Energy Producer (BEP) or an independent public or private organization.
- The VMG Aggregator (VMGA), which would be an association, a company, or simply a software collecting data from the MGs, making and broadcasting decisions to the MGs via the VMGA Portal, as well as operating the communication between the MGs and the MO.
- The Micro-Grids, which are small/medium size entities with possibilities of producing, consuming and storing energy. Examples are a factory, a photovoltaic park or a residence.

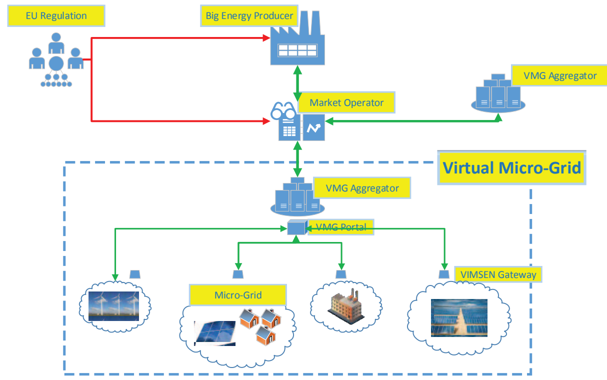

Fig. 2. The VIMSEN Architecture

The MGs are Smart-Grid integrated, equipped with smart meters and a VIMSEN Gateway to communicate their data to the VMGA, receive production day-ahead forecasts from a weather station, and generate predictions for their day-ahead consumption based on training algorithms and historical data[10].

The BEP creates a day-ahead, time-of-use pricing pattern, based on statistical data [11]. Currently, the BEP generally buys energy from small producers at a flat or close to flat price, set by feed-in tariff policies. In order to decrease its operational costs, the BEP decides to buy this energy at a peak-demand time so that the operation of supplementary low-efficiency production plants is avoided. Thus, a "special-price event" is decided where the BEP asks to buy energy at a certain time of the day-ahead schedule, offering a higher price for that particular time. The whole pricing pattern for buying and selling energy is broadcast through the Market Operator to the VMG Aggregators.

We take the perspective of a MG and focus on the MG and VMG level. Two scenarios are studied. The non-interconnected scenario where MGs exchange energy only with the BEP, while the interconnected scenario assumes a set of MGs (forming a VMG) that can exchange energy with each other. This will turn out to be useful for the MGs in meeting their SLA with the BEP in the presence of forecast errors on their prosumption profile.

III. Problem Formulation

The *prosumption profile* of an MG is characterized by a triplet

$$MG = (X, Y, C),$$

where

$$X = (X^1, X^2, \dots, X^{24})$$

denotes the forecasted MG production pattern throughout a day at one hour intervals, with X^i being expressed in kWh,

$$Y = (Y^1, Y^2, \dots, Y^{24}),$$

denotes the estimated MG energy consumption pattern, and

C in kWh is the maximum energy storage capacity of the MG.

The day-ahead pricing pattern for buying/selling energy broadcasted by the MO to the VMG Aggregators is denoted as

$$P = (B, S)$$

where

$$B = (B^1, B^2, \dots, B^{24})$$

denotes the prices (€ per kWh) at which the MG can buy energy from the BEP at each time interval and

$$S = (S^1, S^2, \dots, S^{24})$$

the prices at which the MG can sell energy to the BEP. Each MG applies a scheduling policy (to be discussed in Section IV) that results in its day-ahead Market Decisions captured in the pair

$$MD = (E_b, E_s)$$

denoting the amount (kWh) an MG will buy/sell at each time:

$$E_b = (E_b^1, E_b^2, \dots, E_b^{24})$$

$$E_s = (E_s^1, E_s^2, \dots, E_s^{24})$$

The MG makes an SLA with the BEP to buy and sell these quantities at the specified times and prices. In the case of forecast errors, the MG may not be able to fulfill its SLA, at a certain hour i in which case it will have to pay a penalty. In our performance results the penalty is that if the production is less than the forecasted one by some D_i, the MG will have to buy this amount at price B^i and sell it at price S^i for a cost of $D^i(B^i - S^i)$. Other ways in which the penalty for breaking the SLA (e.g., buying at the spot price) can also be included.

When there are no forecast errors, the daily energy cost of the *MG* is captured by the $COST$ parameter, defined as

$$COST = \sum_{i=1}^{24} [B^i \cdot E_b^i] - \sum_{i=1}^{24} [S^i \cdot E_s^i]$$

IV. Scheduling Policies And Storage Management

In this section we look into scheduling and storage management policies than can be used by an MG (section IV.1) or an association of interconnected MGs (section IV.2).

IV.1 Case of single (non-interconnected) MGs

We first look into the non-interconnected case, focusing on a single MG. We propose nine algorithms that can be used by the MG to make its buy/sell/store decisions trying to satisfy its consumption with the least cost and sell energy to the BEP at the best price, so as to minimize its *COST*. The scheduling and storage management algorithms examined are the following:

1) Uncapacited: the algorithm does not make use of the storage capacity at all. When energy is needed the MG buys, and when energy is produced, it sells.
2) Selfie: the MG tries to be self-sufficient. When energy is produced, the MG stores it. When energy is needed, it consumes from the Storage and if this is empty it buys from the market as much as needed. The MG sells only when its storage capacity is full and can no longer store the energy it produces.
3) Sniper: The MG buys as much energy as can be stored before the "peak demand zone" and stores and sells it all at the special-price event where the sales price is high.
4) Stocky: The MG buys as much energy as it can store, before the "peak demand zone" and uses it to cover its consumption needs in the "peak demand zone" to avoid buying at a high price. The MG sells only when it has more energy than can be stored.
5) Stock 'n' Stock: a variation of Stocky, where the MG buys energy to fill up storage not only before the peak demand zone but also in the low demand zone when the price is low.
6) Conservative: The MG buys energy at the same points with the Stock 'n' Stock but it does not fill up the storage, always leaving a margin of 4 kWhs. Also in "special-price event" it sells only half of the storage.
7) Conservative 70%: The MG buys leaving a 30% margin and sells in the "special-price event" 70% of storage.
8) SmartStock: The MG buys energy at the same points (before the price goes higher) but only as much energy as it expects to be needed by the MG or that it expects to be able to sell. The MG sells in the special-price event only as much energy as it expects not to be needed by the MG in the peak demand zone.
9) SmartStockConservative: It works like SmartStock but is more conservative. It buys and sells half than SmartStock to leave a margin in case predictions are inaccurate.

IV.1.1 Effect of deviations between forecasted and realized production for a single MG

The preceding section considers a Day-Ahead market where an MG trades energy based on the forecast of the previous day. To model the prediction errors, we define a *deviation vector D*, as the difference between the vector $\tilde{X}$ of actual hourly production values and the vector X of forecasted values,

$$D = (D^1, D^2, \dots, D^{24}) = X - \tilde{X}.$$

The cost is no longer that of P, as the MG is forced to buy/sell additional energy at a non-beneficial price compared to the scheduled policy to compensate for the inaccurate production forecast. Thus, the arrays E_b and E_s that define the scheduled buy and sell decisions (SLA) have to be modified to $\widetilde{E_b}$ and $\widetilde{E_s}$, respectively, and the *COST* is modified accordingly:

$$\widetilde{COST} = \sum_{i=1}^{24} [B^i \cdot \widetilde{E_b^i}] - \sum_{i=1}^{24} [S^i \cdot \widetilde{E_s^i}].$$

The performance in the presence of forecasting errors is expected tp be worse than when forecasts are accurate, $\widetilde{COST} > COST$.

IV.2 Case of MGs Interconnected into VMGs: Micro Grid cooperation and Virtual Storage Bank

We now turn our attention to the case where we have n MGs forming a Virtual Micro Grid (VMG). An MG is now able to use the available resources of other MGs in the same VMG so that the additional energy transfers due to non-conformance with the SLAs between the set of the cooperating MGs and the BEP (and thus the corresponding penalties) are minimized. The idea is to create a *virtual storage bank*, consisting of the sum of storage capacities of individual MGs, so that MGs are able to fulfill each other's needs in case of inadequacy of the individual resources. The prosumption profile of a VMG is defined by the component wise addition of the prosumption profiles of its constituent MGs

$$P_{VMG} = \sum_{n} (X^n, Y^n, C^n)$$

In this section, all MGs are assumed to operate according to the SmartStock algorithm (which is the algorithm of choice, based on the performance results in Section V). As the scheduling is based on forecasted calues, the deviation vector of Section IV.1.1 results in the need for the MG to have to buy or sell additional energy to fulfill its Day-Ahead SLA agreement. This results in scheduling (SLA) deviations and the vector of additional energy quantities that have to be bought or sold by the MG is given by:

$$e^b = \widetilde{E_b^i} - E_b^i$$
$$e^s = \widetilde{E_s^i} - E_{s,}^i$$

respectively. When an MG operates as a single entity, energy equal to these deviations needs to be bought/sold by the MG at an additional cost of B^i- S^i per unit of power to fulfill its SLA.

When the MGs form VMGs and cooperate in trading energy, the algorithms running in the VMGA Gateway tries for the scheduling deviations in an MG to be compensated by another MG so that the high-cost energy exchange (SLA penalty) with the BEP is avoided. Thus, the objective of the VMG is to ensure that the overall energy exchanged (sold / bought) between the VMG and the BEP is almost equal to the quantities scheduled at each hour, so that the individual SLAs are met, i.e., that the total energy difference resulting from the scheduling deviations for a VMG should be close to zero at each hour (componentwise):

$$\sum_{k=1}^{n} [\widetilde{E_b^i}{}^k] - \sum_{k=1}^{n} [E_b^{i\ k}] \rightarrow 0$$

$$\sum_{k=1}^{n} [\widetilde{E_s^i}{}^k] - \sum_{k=1}^{n} [E_s^{i\ k}] \rightarrow 0$$

IV.2.1. Grouping of the Micro Grids into Virtual Micro Grids according to the correlation of their production patterns

An important issue affecting the algorithms' performance and the MGs' ability to meet their SLAs through collaboration is related to the way MGs are grouped together into VMGs. Useful in this context is the concept of "MG production correlation".

An MG A will be said to be positively correlated to a MG B when their production patterns are affected by weather and other conditions in the same way, or more mathematically, if their deviation vectors have strictly positive crosscorrelation,

$$E(D_A * D_B) > 0,$$

where * denotes inner product and $E(\,)$ expected value. An example of positively correlated MGs would be a set of solar parks located in nearby geographical areas, where a loss of sunshine would affect MG production patterns in similar ways. MG A will be said to be negatively correlated to MG B when

$$E(D_A * D_B) < 0$$

MG A will be said to be uncorrelated to MG B, when their production sources are independently affected,

$$E(D_A * D_B) = E(D_A) * E(D_B) = 0,$$

where we assume unbiased estimators, $E(D_A)$=$E(D_B)$=0. In the performance results of Section V we examine the cases where a VMG consists of a) maximally positively correlated MGs, b) uncorrelated MGs and c) pairs of negatively correlated MGs.

V. Performance Evaluation Results

In this section we evaluate the algorithms' performance under a variety of conditions and scenaria. The performance results for the single MG (non-interconnected) case are presented in section V.1 along with the effects of the deviation vector defined in V.1.1. The profits that can be obtained through the cooperation among MGs that form VMGs along with the role played by the correlation factor are investigated in section V.2.

V.1 Case of Single (non-interconnected) MG

The resource management algorithms of section IV.1 were implemented in MATLAB, using production, demand and storage capacity data derived from random uniform distributions within a range of realistic energy patterns.

More precisely, each *MG* profile (X, Y, C) was implemented by drawing from uniform distributions as follows:

- the forecast X^i for the energy produced by the MG during hour *i*, was uniformly distributed in the range 7-30 kWhs, independently for different *i*'s;
- the forecast Y^i for the energy consumed by the MG during hour *i*, was uniformly distributed in the range 7-30 kWhs, independently for different *i*'s;
- the Storage Capacity *C* of an MG, was chosen as a constant in the range of 0-30 kWhs, and was different for different MGs.

Regarding the prices used in our performance evaluation results we used datasets containing realistic data derived from the Greek National Energy Provider Company (PPC) pricing patterns, presented in Figure 3.

In each experiment, an algorithm takes as input the profile *MG=(X,Y,C)* of the Micro Grid and the data for the day-ahead pricing P=(B, S). The results we describe were averaged over 10,000 experiments performed. The brief average scoreboard in cost (euros per day) is presented in Table 1 for all the algorithms examined. SmartStock algorithm achieves the best results in every scenario, significantly outperforming the Uncapacited, which interestingly is the policy applied in the majority of RES plants of today.

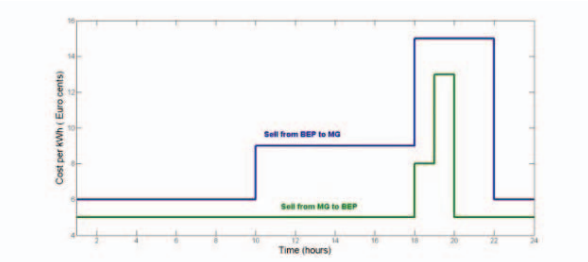

Fig. 3. Pricing patterns

TABLE I. AVERAGE COST PER 24H FOR ALL ALGORITHMS EXAMINED FOR THE CASE OF A SINGLE MG, WHEN THERE ARE NO DEVIATIONS BETWEEN THE FORECASTED AND THE ACTUAL PRESUMPTION PROFILE

Algorithms	Average Cost (€ per day)
Uncapacited	13.160
Selfie	1.445
Sniper	0.769
Stocky	1.307
DoubleStock	1.238
Conservative	1.026
ConservativePerCent	0.997
SmartStock	0.690
SmartConservative	1.019

V.1.1 Effect of deviations in production profile

We then evaluated the performance of the algorithms in the case the forecasted production profile differs from the production profile actually realized by the deviation vector D, considered to follow a random uniform distribution within a range of +/- 25%. The results are presented in Table 2. The performance results obtained in this case are worse, as expected, except for the Uncapacited algorithm which could not be affected, as it was not making use of any actual strategy in the first place. The SmartStock algorithm still achieves the best performance.

V.2 Case of Multiple MGs Interconnected into VMGs

In this section we present the performance results obtained for the case where multiple MGs cooperate into forming a VMG. A VMG consisting of n cooperating MGs with different (randomly distributed) storage capacities, production and demand patterns was implemented within realistic pattern margins. The MGs compensate their energy needs either on their own, by exchanging energy with the BEP (as in the previous section), or by cooperating and applying the concept of the virtual storage bank (as a VMG). In each case the daily cost per MG was calculated resulting in two values, the average daily cost per MG when they do not cooperate, denoted as $Cost^{non-coop}$, and the average daily cost per MG when they cooperate in a VMG, denoted as $Cost^{coop}$. The difference between these values gives the daily monetary profit that each MG gains on average by cooperating in VMGs. The percentage profit ("value of cooperation") is defined as:

$$\text{Value of Cooperation} = (Cost^{non-coop} - Cost^{coop}) \cdot 100 \; / \; Cost^{non-coop}$$

We are particularly interested in the criteria used for selecting the MGs that participate in the same VMG. To cluster MGs into VMGs we used the correlation between their production profiles, as discussed in section IV.2.1.

TABLE II. AVERAGE COST PER 24H FOR ALL ALGORITHMS FOR A SINGLE MG, UNDER RANDOM 25% DEVIATIONS BETWEEN THE FORECASTED AND THE ACTUAL PRESUMPTION PROFILE.

Algorithms	Average Cost
Uncapacited	13.160
Selfie	2.809
Sniper	0.906
Stocky	1.410
DoubleStock	1.346
Conservative	1.162
ConservativePerCent	1.126
SmartStock	0.827
SmartConservative	1.148

The Value of Cooperation is calculated for different numbers n of cooperating MGs and presented in Table 3. The results are plotted in the same graph for the three correlation cases in Figure 4. From the results it is demonstrated that negatively correlated MGs exhibit a profit of the order of 15.5-16.5%, when cooperating. This gain increases somewhat when n increases. This was expected since in the latter case the production of one MG serves as a "hedge" for the production of the other when forecast errors occur. The profit is significantly smaller in the case of independent MGs (starts at 6.45% when n=2 but increases rapidly with n) and approaches that of negatively correlated MGs for large n. Thus, a higher number of cooperating MGs results to a higher profit per MG when the MGs are independent. Interestingly and rather surprisingly, there is also a positive value of cooperation (rather modest, of the order of 2.1%) even for maximally positively correlated MGs indicating that such MGs can still benefit from cooperation. The gains of cooperation therefore also come from MGs pooling their resources together. When the MGs are positively or negatively correlated, increasing n also helps but has diminishing returns after a certain point. This means, that in terms of storage sharing, small MG coalitions are good enough when the MGs are positively or negatively correlated, but larger coalitions are needed when the MGs are independent.

TABLE III. VALUE OF COOPERATION (PROFIT PER CENT) FOR N MGS

Value of Cooperation (profit %)	n=2	n=6	n=10	n=20	n=40	n=60
Positive correlation	2.10	2.85	3.55	3.45	3.73	4.21
Null correlation	6.45	11.12	12.66	13.77	14.70	15.23
Negative correlation	15.45	15.77	16,33	16,39	16.42	16,60

VI. CONCLUSIONS

We proposed scheduling algorithms that can be used by an MG to benefit from the time of use market scheme, and studied the benefits that MG cooperation can provide for the case of multiple Micro Grids forming coalitions. A profit of up to about 16,6% can be gained from the MG cooperation.

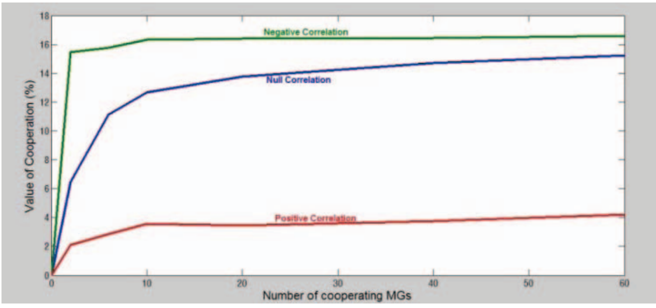

Fig. 4. Value of Cooperation (profit per cent) for n MGs

The benefits of cooperation are higher when the MGs forming a VMG have negatively correlated production patterns and they can also become equally high even when the MGs have independent production patterns, by increasing the number of participating MGs. The profit would be more significant if other techniques, such as Demand Response (DR) and Supply Response (SR), were applied. Future research will be carried out to investigate the profits that can be obtained by empowering, through cooperation, the negotiation power of MGs that could thus become a more significant player in the energy market.

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