Demand Allocation in Local RES Electricity Market Among Multiple Microgrids and Multiple Utilities Through Aggregators

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***Abstract*—The electricity market for Renewable Energy (RE) Sources (RES) has to be transformed into a market that is more competitive and decentralized than the current one, given the failure of subsidy policies, like the Feed-In-Tariff (FIT) policy, and the increase in the number of small producers but also in the number of power utilities. Clearly, each utility must follow regulation rules regarding the proportion of RES units it must have in its energy mix, in order to avoid emission penalties. Following a decentralized market scheme, we address the problem of allocating a total amount of RE demanded by a set of utilities in a local market to individual RES microgrids (MGs) that can cover the demands, considering two supply policies. In the first policy, a RES producer is assumed to be able to split its production into smaller parts so that it can supply multiple utilities, and a simple allocation algorithm is presented. In the second policy, a RES producer, due to market or technical constraints, cannot split its production and share it among utilities. In this case, we provide an algorithm that solves the problem effectively by viewing it as a knapsack problem. If the cost functions of MGs are independent of the utilities to which they sell (e.g., negligible transportation costs), the results show that the non-divisible policy slightly benefits the MGs. However, in a decentralized market, it is natural to assume that the cost functions of the producers depend on the location of the utilities. To account for this, we provide two more allocation algorithms under both examined supply policies. In this case, the non-divisible policy is much more profitable for MGs and, moreover, the entrance of new utilities in the market clearly benefits them over the divisible case.**

Index Terms—Knapsack, Demand Allocation, Multiple Utilities, Local RES market, Microgrids

I. Introduction

The electricity market is currently undergoing an extensive transformation with the opening of the market to new players and the evolvement of the smart grid. An increasing number of small-scale producers, which generate energy mainly by renewable means is entering the electricity market. This forces the RES electricity market to become decentralized, since centralized techniques are ineffective in handling numerous small generators. Moreover, current regulation raises the entry barriers for the participation of a producer in the electricity market, by posing capacity thresholds that he must obey. A technique to address both of these requirements is to aggregate small (and probably geographically close) generators into larger groups and then let each group participate in the local electricity market as a single entity. For example, in [1] a software platform provides access of Distributed Energy Resources (DERs) to the electricity market. This platform creates an internal market for the participant aggregated DERs, where it acts as a market operator as well as a service operator.

While the decentralization of the current market is beneficial for the participation of small distributed generators, the continuation of current subsidy policies, like the Feed-In-Tariff (FIT) [2] is unsustainable. In particular, since with FIT power utilities are forced to buy the entire amount of RE of the producers at prices higher than the market ones, the electricity price paid by end consumers increases rapidly as more RE generators enter the market. Thus, more competitive market-oriented schemes need to be adopted to sustain and increase the penetration of the RES sector in the total energy mix. At the same time, RES producers find it hard to directly participate in the electricity market as it currently stands. Their high startup required investment in combination with their low marginal costs, their intermittent nature and the volatility of electricity prices makes RES investments extremely risky and unprofitable in the absence of subsidy policies. Nevertheless, as technology evolves RES installation costs are rapidly diminishing leading to the possibility of moving to a more competitive RES-alone electricity market, without the need of generous subsidy policies that tend to create bureaucratic mentalities and inefficiencies.

Market models that involve the use of aggregators lie at the heart of research for the future smart grid. In [1] a decentralized architecture is presented, where a virtual aggregator (a software-based platform) allows MGs to trade electricity among themselves and the main market operator, but no further analysis for pricing schemes or other practical concerns are made. In [3] , a two stage market model is introduced for MGs' power transactions, in which model an aggregator acts as a mediator between the MGs and the power utility. The paper analyzes the pricing conditions for the aggregator and the MGs so that they both gain by such a scheme. In [4] an interesting approach for demand shaping is presented, where the utility gradually increases monetary compensation to aggregators, who compete in offering their demand shaping units. Each aggregator compensates its customers for providing their units. In this scheme, it is shown that the most willing users do not derive the maximum benefits. In [5] using a game theoretic framework, authors form coalitions that minimize distribution losses between the coalitions and the macro-station.

While some of the above works consider a decentralized market, their main limitation is that they assume that the buyer's side consists of only one power utility (or macro-station). However, even though the RES sector is not yet fully evolved, countless distributed generators are expected to enter the future

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electricity market, suppressing the price of the RES units and leading to fully competitive environments. In this setting more power utilities, each with its individual demand for RE, will enter the market forming a supply-demand allocation problem. In the current electricity market, regulation rules force power utilities to cover a certain portion of their total demand from RES in order to achieve environmental goals. This means that all individual demands for RE must be sufficiently satisfied so that no utility faces the threat of paying CO_2 and other GHG emission penalties. In this situation the goal of the market is to determine the energy units that should be generated by the producers and how those units should be allocated in order to meet the individual demands of the utilities.

To the best of our knowledge no work exists in literature that provides an algorithm to satisfy the specific RES demand constraints of each utility in a market based approach. Rather, most works focus on meeting the required demand or other system constraints centrally, a problem referred to as the *optimal generator dispatch* or *unit commitment problem*. A survey on solutions for the unit commitment problem can be found in [6] . In the present paper, using the architecture of [1] where the aggregator coincides with the market operator (MO), we present four algorithms for demand allocation among multiple RES generators and multiple utilities. In particular, we considered two supply policies that might exist in the electricity market and two cases for the cost functions of microgrids for deriving the appropriate algorithms. In the first case of the (*divisible case*), each producer is assumed to be able to split its supply into smaller parts and sell them to more than one utility. In the second case (*non-divisible case*), the microgrids are not allowed to split their supply and we use algorithms based on the knapsack problem [10] in order to perfectly match the individual demands. Regarding the cost functions, in the first case we assume that they are independent of the utilities to which energy is sold, and therefore the aggregator needs to only consider the supplies of the MGs and the demands of the utilities. In the second case, the cost functions of MGs depend on with the location of each utility, meaning that for the same MG and different utilities the cost functions are different. This is a real scenario to be considered in a decentralized market that needs also to reduce the overall path losses of the system.

In section II we describe the multiple utilities environment and a distributed algorithm for acquiring the supply bids that cover the requested demand is provided. In section III we present the four algorithms that distribute the supply units to match the multiple requested demands of the utilities. Finally, in sections IV and V results and conclusions are presented, respectively.

II. SYSTEM MODEL

A. Multiple Utility Market

A liberalized market, in addition to the integration of many small scale producers, also includes multiple power utilities, comprising the retail market (Fig. 1). In such an environment, both consumers and producers can choose among many power utilities to buy and sell energy, respectively. This will lead to market benefits from the producers perspective, since the opportunities to sell their energy supply will increase.

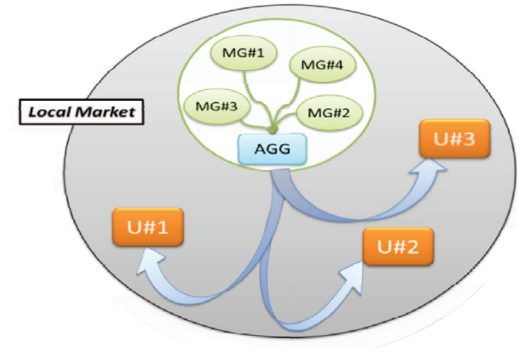

Fig. 1:Multiple Utility Market Model

Well known environmental concerns (Greenhouse effect) impose certain regulations on the electricity market in order to promote the usage of renewable energy. EU obliges its countries to include at least 20% from RES within their entire energy consumption, or otherwise be subject to high penalties [7] . In another EU regulation directive that drives the RES market, power companies (or utilities) that use obsolete generators are penalized for CO_2 emissions. Thus, the demand for RE mainly comes from regulatory constraints that are hard for power companies to avoid. In this paper, following the current trend, we consider the problem where each utility needs a given amount of RE in order to meet regulation rules and avoid monetary penalties. We let M be the number of RES producers and N be the number of power utilities in the same market (which may be a local one). We let D_j be the amount of RES units requested by the j-th power utility, and $X_{i,\max}$ be the maximum energy that can be produced by the i-th RES producer. We also let d_j be the amount of RES units actually bought by the j-th power utility and x_i be the energy actually sold by the i-th RES producer. Then, the following equation should be held:

$$\sum_{i=1}^{M} X_{i,\max} \geq \sum_{i=1}^{M} x_i = \sum_{j=1}^{N} d_j \geq \sum_{j=1}^{N} D_j = D \qquad (1)$$

Naturally, we assume $\sum_{i=1}^{M} X_{i,\max} \geq \sum_{j=1}^{N} D_j$ so that we have a feasible problem instance. This is also a prerequisite if liberalized markets are to be adopted. However, as explained earlier, the participation of RES producers in the current electricity market along with conventional producers is practically infeasible mainly because the former ones, being small (thus, price takers) and having at the same time low marginal costs would be forced to sell at very low prices (RE that is not sold or used, is lost in the absence of storage). However, it is possible to allow RES producers play competitively in a RES-only market and enable generation of a revenue stream to them, without being affected by competition of conventional producers. The justification for the separation of the RES marker from the conventional electricity market is that renewable energy is qualitatively very different than that of fossil fuel generators. This is because RES units offer very significant positive environmental and geographical externalities that are difficult to account for in the market.

Following the decentralized scheme of [1] , we assume that RES MGs in a given geographical area are virtually aggregated through a software platform. Then, the aggregator, who also acts as a local RES Market Operator, is addressed by power utilities operating in the area to sufficiently supply them with a certain amount of RE to satisfy their corresponding demand as defined mainly by regulation rules (environmentally sensitive consumers may also generate additional demand, by being willing to pay extra for RE). As market operator, the aggregator, similarly to the typical electricity market, collects the supply bids of the RES MGs that participate in the local market and at the point where the aggregated supply meets the requested demand, it announces the final price for the RES units as well as the set of the MGs that will supply the grid. The outcome of the aforementioned procedure determines the market prices that the utilities need to pay in the local RES electricity market in order to obtain the requested RES units. This procedure can be performed on a daily, hourly, or other specified time interval unit-ahead policy. The supplies of each producer might come from the distributed algorithm described in section II.B.

B. Aggregator's Optimization Problem

Aggregator's target is to allocate generated energy units from RES producers to corresponding RES demands of the utilities, that is, find the amount x_i of units each RES producer (or MG) i will sell and the amount d_j of units each utility j will buy to meet its demand D_j ($d_j \geq D_j$). Two different cases are investigated. In the first case, we assume that each MG can sell its energy units to one or multiple power utilities at a given time period. This represents a divisible supply model, where supplies can be continuously split into smaller quantities and be sold to different buyers. In the second, non- divisible case, the supply of each MG can be allocated only to one power utility. This may be derived from technical considerations or from business models and competition policies among different power utilities. We assume that the non-divisible constraint is valid only within a time period. Thus, our problem is to decide the quantities x_i, i=1,2,…,M, of units generated by the MGs in a way to best satisfy the demands D_j, j=1,2,..,N, of the different utilities.

In a liberalized market, each producer is self-sustainable and competes against the other producers in order to achieve a satisfactory share in supplying the electricity market. More specifically, in this model, many producers have an insignificant share of the market and are too small to affect the market price via a change in market supply (they are, as we say, "price takers"). Nevertheless, each one of them wants to achieve the highest possible profits, while the aggregator needs also to meet the constraint. Therefore, supposing that λ is the market price announced by the aggregator, x_i is the supplied amount in units, $C_i(x_i)$ is the production cost of generating those x_i units, the optimization problem of the market (aggregator) can be written as:

$$\max_{x_i}\{\lambda \cdot \sum_{i=1}^{M} x_i - \sum_{i=1}^{M} C_i(x_i)\},$$
$$\text{s.t. } \sum_{i=1}^{M} x_i = D,\ 0 \leq x_i \leq X_{i,\max} \quad (2)$$

where $X_{i,\max}$ is the maximum amount of units that the i-th MG can produce in the given time interval (capacity) and $D = \sum_{i=1}^{M} D_j$ is the aggregated demand. The cost $C_i(x_i)$ of each MG is assumed to be a quadratic polynomial as [8] indicates:

$$C_i(x_i) = \begin{cases} b_i \cdot x_i + a_i \cdot x_i^{\,2}, & 0 \leq x_i \leq X_{i,\max} \\ \infty, & \text{otherwise} \end{cases} \quad (3)$$

It is possible to relate the parameters b_i and a_i to installation and grid network parameters as discussed in [9] . Particularly, b_i is derived from installation costs of the investment and a_i is the transportation costs due to power losses of the delivery. Supposing that $V_0, R_0(l)$ are the voltage and resistance of the power line of length l, respectively, a_i can be computed as:

$$a_i(l) = b_i \cdot R_0(l)/V_0^2 \quad (4)$$

In this case the cost of the i-th MG is dependent on its distance the j-th utility. That is the cost of i-th MG is different for two different utilities u_1, u_2: $a_i(l_{u1}) \neq a_i(l_{u2})$. Moreover, since we must have $x + R_0(l)/V_0^2 \cdot x^2 < X_{i,\max}$ we get for the maximum quantity that can be offered:

$$X'_{i,max}(l) = \frac{V_0^2 \cdot \left(-1 + \sqrt{1 + 4 \cdot \frac{R_i(l)}{V_0^2} \cdot X_{i,max}}\right)}{2 \cdot R_i(l)} \quad (5)$$

This means that the maximum supplies that an MG can offer to various utilities are different.

In the usual case where the microgrid producer is also a consumer (a so-called *prosumer*) the amount of energy it offers for sale can increase by lowering its own consumption. In that case the cost function $C_i(x_i)$ for offering an amount x_i of energy for sale will also depend on the "degree of annoyance" the prosumer suffers by not consuming some of its produced energy, offering it for sale instead. This annoyance is often modelled as a quadratic function, and its effects can be included in and alter the parameters b_i and a_i [4] .

Equation (2) can be solved in a de-centralized way allowing the MGs to preserve their cost function as private information. This feature allows flexibility for MGs to offer their units using more sophisticated practices, like techniques from game theory. Additionally, de-centralized optimization simplifies the realization, since the aggregator only needs a few bits in order to exchange information about the supplies that the MGs are willing to offer, while the MGs need only know the market price $\lambda(k)$ at each iteration k. Then, each producer tries to maximize its profit Π_i obtained by solving the following equation with respect to production x_i:

$$max_{x_i}\{\Pi_i = \lambda(k) \cdot x_i - C_i(x_i)\} \quad (6)$$

Eq.(6) can be easily solved through differentiation provided that the capacity constraints are satisfied, that is, x_i must belong to [0, $X_{i,\max}$]. In particular, if $b_i<\lambda(k)$, then production x_i is negative, which obviously is not feasible for MG to produce, and thus is set equal to 0. In contrast, if the x_i is larger than $X_{i,\max}$, then the output x_i is limited to $X_{i,\max}$ since the MG cannot produce more than its capacity The control of the output x_i sold is not directly performed by switching on or off the PV panels; rather the MG chooses either to consume the additional units onsite, or to store them (e.g., in order to generate more profits by offering those units at time frames that are more favorably priced. The aggregator, after collecting the supplies of the MGs, updates the market price according to:

$$\lambda(k+1) = \lambda(k) + \varphi\,[D - \sum_{i=1}^{M} x_i] \quad (7)$$

where scalar φ is an appropriate step parameter and D is the aggregated demand requested by the power utilities. The above iterative process stops when demand D is satisfied. Eq.(6),(7) constitute the "Distributed Market Algorithm" (DCA), in which non-negativity and capacity constraints are also considered in the final solution.

C. Price set by the aggegator

Using the decentralized process, the aggregator can obtain the quantities that the local MGs are willing to supply to the local utilities to meet their required RES demand(s). Since the MG's supply is determined by Eq. (7), this means that they are essentially price takers (their supply is such that their marginal cost is equal to the price offered, while satisfying the constraints). When the aggregator "faces" the utilities, however, it is no longer a price taker but a monopoly (or an oligopoly in case there are several aggregators). It is, of course, a regulated monopoly. A justification for allowing a monopoly for the aggregator against the utilities in the RES energy market is as follows. RES production offers two kinds of positive externalities. First, RES electricity provides environmental benefits since its generation of energy is emission-free. This feature directly leads also to economic benefits since energy regulators penalize producers with CO_2 emissions. Second, MG production is usually close to the consumers, thus avoiding a) transportation losses and b) big investments needed for improving the distribution network. If the RES energy was sold at "normal" market prices, these positive externalities would benefit the other market players (e.g., DSO) and the RES producers would get nothing out of it. Thus, the aggregator could be allowed by regulation to sell the electricity to the utilities at a price higher than λ (e.g., $1.5 \cdot \lambda$ or whatever percentage parameter, mark-up from the marginal cost of RES energy, the regulation permits). That is, when the aggregator negotiates with the microgrids it offers price λ to them, but then when it offers this quantity to the utilities it offers it at price $1.5 \cdot \lambda$. In our results we do not consider such a price mark up, even though we believe it should be included in practice to benefit RES producers in the absence of FIT and other subsidy policies. This price markup should account not only for the positive externalities of RES production, which could then be distributed among RES producers based on their contributions in energy units or based on any other desired policy, but also for the operating costs (and possible profits) of the aggregator.

Having determined the price at which the energy will be offered by the aggregator to the utilities, the next problem is to decide which MG's generated units will supply which utility. In the next section we provide the proposed algorithms that deal with this problem.

III. DEMAND ALLOCATION IN MULTIPLE UTILITIES

Having determined the RES units to be produced by each MG, the aggregator should then try to assign the production units of the M RES MGs to the N utilities so as to meet their demands with the least deviations. That is, the supplies must be allocated among utilities to minimize the deviations from the desired demands. If the cost functions of the MGs are independent of the utility to which they sell (e.g., negligible transportation costs) and the MG supplies are indivisible, the aforementioned problem can be viewed as a form of multiple knapsack problem "MKP" [10] , which is actually a hard computational problem. In the divisible case, where an MG can sell its production to multiple utilities, the problem is much simpler than in the non-divisible case. If the cost functions of the producers depend on the utilities to which they sell their supply, then MKP can again be used in order to make the allocation. In the next subsections, we first describe the MKP as a preliminary step to our solution for the non-divisible case. Then, we provide our solutions for the two policies if the costs are assumed to be unrelated to the power utilities and in the last subsection we discuss the algorithms for cost functions related to the location of utilities.

A. The Knapsack Problem

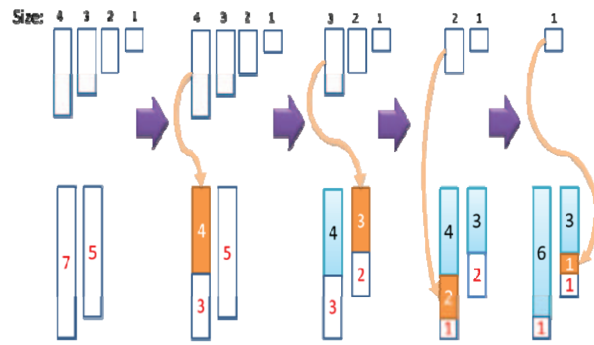

Fig. 2: An example for solving a Knapsack Problem using Best Fit

In the typical MKP, items of different sizes need to be assigned to a subset of bins with certain (possibly different) capacities. The goal of MKP is to assign the items into the bins without exceeding any bin size constraint. For the single dimensional MKP, many heuristic methods exist to solve this problem. A common approach is the Best Fit (BF) method [10] , which is efficiently used for the bin packing problem, a variation of MKP. In this algorithm the "items" are firstly sorted by size and, then, are sequentially allocated to the "bin" that has the largest residual capacity. An illustrative example of BF algorithm is depicted in Fig. 2, where we have "items" of sizes 1,2,3,4 and two "bins" with capacities predefined to be equal to 7 and 5, respectively. The steps of BF algorithm are as follows: a) the items are first sorted by size in decreasing order: (4,3,2,1). b) Then, the item with the largest size (4) is allocated to the bin with the largest residual capacity (bin#1), which is left with a residual capacity of 7-4=3. If multiple bins have the same residual capacity, then the bin is randomly chosen. c) The next largest item (of size 3) is allocated to the largest residual capacity. Thus, the second bin (bin#2) receives the 3 unit item and is left with residual capacity of another 5-3=2 units. d) The next largest item (of size 2) is assigned to the bin with the largest residual capacity, that is the bin#1, which now has residual capacity 1 unit (3-2=1). e) Finally, the remaining item (of size 1) is assigned to the second bin (which has residual capacity of 2). The final allocation of units in the bins is [4+2,3+1]=[6,4]. If more parameters are also considered in the problem, like costs or profits, then the multidimensional MKP arises. In this case, the problem can also be solved using an approach similar to the single dimensional case. The only difference with the previous algorithm is that the optimization of the parameter is of primary consideration. That is, the items are first sorted by the parameter (instead of size) in ascending order (if minimization is the objective to be achieved) and the allocation to the bins is then based on capacity constraints.

B. Multiple Allocation with costs Independent to Utilities

In the next two subsections, we assume that the supply of the MGs in the market is obtained by applying the DCA for the aggregated demand (eq.(2)). The aggregated demand can be used since the supply bids of the MGs are independent of the utilities (i.e. the location of utilities does not affect the cost functions). It should be noted that while other market models can also be used by the aggregator in order to determine the RES supplies and market price, nevertheless the use of the proposed algorithm bears in mind a liberalized market.

1) The divisible case

The intermittent nature of RES generation and also the varying utility demand might result in many partitions of generated energy throughout the day, making possible to supply the utilities at different time periods from different RES producers. Moreover, in other liberalized markets the suppliers might choose to sell different portion of their total production to different retailers. Similarly, if we assume an advanced power line where a RES microgrid is technically allowed to split its production so as to supply different power utilities, the aggregator solves the demand allocation problem relatively easily, by sequentially allocating the individual supplies x_i to the utilities. If a supply exceeds an utility's demand, then, the aggregator instructs producer to split its production in two parts allocating the second part to the next utility. For example, let us assume that 2 utilities, u_1, u_2, exist in the market with demands 3,4 respectively and that the supplies for the aggregated demand 3+4=7 come from four MGs with generation 2,2,3 respectively. Recall that the supply units come from the DCA. Then the first producer allocates its 2 units to the first utility, u_1. Second producer allocates 1 unit to the first utility (who now covers its demand) and the leftover 1 unit of its generation is "cut" and allocated to the second utility, u_2. Obviously, the supplies of the remaining producers will be allocated to the second utility.

2) The non-divisible case

If, in contrast, we assume that each RES microgrid is obliged from bilateral contracts or from system requirements to supply one and only utility, then the non-divisible policy arises. In this section we make the assumption that the cost functions are independent of the utilities. In this case, as already stated, the problem of assigning the microgrid supplies to the multiple utilities can be viewed as a MKP. In particular, the supplies are viewed as the "items", while the utilities are viewed as the "bins" with their "capacity" being their corresponding individual requested demand. Then the problem can be addressed by simply applying BF method with a slight modification. In particular, since the satisfaction of the requested demand(s) D_j must be secured, the BF must allow the largest "item" to be allocated to the "bin" with the maximum residual "capacity" even if it exceeds it.

In order to have a meaningful allocation, the aggregator should try to allocate each MG to the utility that allows it to generate more profits. Apart from this, the aggregator should firstly use the most efficient MGs, which offer their units at the cheapest price. This is essential in order to retain an efficient market that uses the cheapest units to cover the demand. Therefore, the aggregator solves the demand allocation problem as a two-dimensional MKP with the second dimension being the individual profits Π_i [see eq.(6)] of each MG. That is, after obtaining the supplies x_i of the producers (from DCA), the aggregator, using the BF algorithm tries to assign them to each utility, while also trying to best satisfy the objective of maximizing the profits. In particular, the aggregator sorts MGs by profits, Π_i, in decreasing order (recall that x_i*'s* and Π_i*'s* have already been obtained using DCA) and, then, sequentially allocates the most profitable MGs to the largest residual demands. This process is repeated until either all demands are satisfied or all the supplies have been allocated. If multiple MGs have equal profits, then the aggregator selects the MG with the largest supply as the next item to be allocated, since this MG offers at the same price a bigger quantity. Due to the non divisibility constraint and due to the fact that the obtained (pre-allocated) supplies meet the exact amount of the aggregated demand, some of the utilities, after the allocation, might be oversupplied (i.e. the demand covered by MGs and the demand requested by utilities are not precisely matched $d_j \geq D_j$). Therefore, an additional algorithm is needed in order to adjust the supplies and eliminate any deviation from the demands.

Microadjustments

The assumption of non divisible supplies has as a result that the supplies allocated to the utilities may deviate from their requested demands, and some utilities may be oversupplied. Therefore, an algorithm that performs micro-adjustments is needed in order to more precisely meet the requested demands. In particular, for a given utility u_j that has been allocated $d_j \neq D_j$ units of energy, we let S_j be the set of MGs that allocate their supply to it. We then perform the DCA in this cluster for utility's specific demand D_j:

$$\max_{x_{ij}} \left\{ \lambda_j \cdot \sum_{i \in S_j} x_{ij} - \sum_{i \in S_j} C_i(x_{ij}) \right\},$$
$$s.t. \ \sum_{i \in S_j} x_{ij} = D_j, \ \ 0 \leq x_{ij} \leq X_{i,\max} \tag{8}$$

where x_{ij} is the amount of energy sold by producer i to utility u_j. In this way, the price λ_j is different for each utility u_j and the supplies x_{ij} of microgrids i to the utilities u_j are redefined so that the demand D_j is precisely met ($\sum_{i \in S_j} x_{ij} = d_j = D_j$). After the end of this procedure, no deviation for demands will exist and the market price that satisfies all the demands is the largest from λ_j, since at this price all demands are met. The full algorithm for demand allocation in a multiple utilities environment is illustrated in Table I.

Table I: Pseudocode of algorithm for divisible case and cost function independent from utilities

1. Collect all the x_i's for aggregated demand $D = \sum_{j=1}^{N} D_j$, where $j=1,2,...,N$ the utilities and $i=1,2,...,M$ the MGs in the market using DCA.
2. Sort the MGs that supply the D units by profits Π_i in decreasing order to the list *list[M]*. For MGs with the same profits sort them by size in decreasing order.
3. Sort the remaining MGs by solving (6) with respect to $\lambda(k)$ and for $x_i = X_{imax}$. That is for each MG there is a λ_i announced to the aggregator. This is essential in order to cover the undersupplied utilities ($d_j < D_j$).
4. Initialize residual demand $rd_j = D_j$, list of allocated MGs: $AMGs[1:N] = \{\emptyset\}$
5. Set i=1.
6. Until all $rd_j = 0$ are ,
   6.1. Allocate MG_i=*list*[i] to Utility U_j with the largest residual demand rd_j : $AMGs[j] = \{AMGs[j] \cup MG_i\}$.

6.2. Update residual demand of U_j: $rd_j=rd_j-x_i[MG_i]$
6.3. Update $i=i+1$.
7. Make the microadjustments:
7.1. Use DCA to calculate the price λ_j and the supplies x_{ij} for demand D_j and for MGs= $AMGs[j]$ [see eq.(8)].
8. Set market price $p=\max\{\lambda_j\}$.

C. Multiple Allocation with costs dependent to Utilities

If the location of the utilities plays a role and has to be accounted for in the cost function, the allocation problem becomes more complicated. In particular, due to the different locations of the utilities, the transportation cost of the energy sold by an MG depends also on the utility to which it is sold. As a result, the offered supplies by an MG exhibit a different cost function for each utility. Additionally, each supply offered by an MG to a utility dynamically affects the supplies of the same MG to other utilities. Lastly, in this case, the maximum supply (capacity) of an MG also depends on the utility to which it is sold. In the next subsections, we describe two iterative algorithms to address these complications.

1) The divisible case

In the divisible case the MGs are affected not only by the supplies of other MGs, but also from their own supplies to the various utilities. This is because the maximum capacity of a MG is a constraint imposed over all supplies of this MG. As a result, the supply of an MG that is given to one utility affects the maximum capacity that the same MG can offer to the other utilities. Due to the dynamic nature of the problem, it can only be solved iteratively. Again the aggregator's concern is to allocate each MG to the utility that maximizes its profits. Note that if the parameters b_i are equal, this objective is equivalent to the minimization of the transportation costs. The problem can be viewed as a two-dimensional MKP, as in subsection III.B.2, with the profits of the MGs being the second dimension. In particular, by running DCA for each utility (i.e., for each D_j), the aggregator obtains the supplies x_{ij} as well as profits Π_{ij} of all MG for each utility and the price λ_j. Note that the profits and the supplies of each MG vary depending on the utility. Then, the aggregator for each MG sorts the utilities by profits in decreasing order. After the sorting, it allocates the corresponding supplies to the utilities sequentially beginning from the most profitable. However, each allocation reduces the maximum amount that can be offered from the same MG to other utilities. Note that this in turn affects the supplies of other MGs. Therefore, after each allocation, the aggregator needs to assert whether any maximum capacity constraint is violated.

For example, let as assume that for an MG with maximum capacity $X_{i,max}$ (not location-based) and 3 utilities we have that $x_{i1} = x_{i2} = x_{i3} = X_{i,max} \cdot \frac{3}{4}$ and $\Pi_{i1}>\Pi_{i2}>\Pi_{i3}$. Then the aggregator allocates the x_{i1} to the first utility. However, the supplies to other utilities are affected by this allocation, since its maximum capacity is now $X_{imax}/4$. Therefore the supplies are reduced to $x_{i2} = x_{i3} = X_{i,max}/4$. By allocating the second supply to the next profitable utility, there is no unit left for the third utility. The final allocation to utilities (in this iteration) is $[0.75, 0.25, 0] \cdot X_{i,max}$. Obviously, this allocation affects supplies of other MGs to the other utilities and, thus, this process needs to be performed multiple times until the constraints are all met and a valid result is derived. The market price is the price that satisfies all the demands, which is the largest of λ_j. The full algorithm is presented in Table II:

Table II: Pseudocode of algorithm for divisible case and cost function dependent on utilities

1. Set $X_{ij}=X_{ij,\max}$ (the location based maximum capacity[see (5)]) and obtain the not-location based capacities, X_{imax}, where $j=1,2,\ldots,N$ the utilities and $i=1,2,\ldots,M$ the MGs.
2. Repeat
  2.1. For each demand D_j
    2.1.1. Calculate supplies of i-th MG, x_{ij} , and price λ_j for maximum supplies X_{ij}, using DCA
    2.1.2. Add the supplies of each MG: $Y_i = \sum_{j=1}^{N} x_{ij}$
    2.1.3. If none MG violates its maximum supply $X_{i,\max}$: $Y_i \le X_{i,\max}$, then go to 3
    2.1.4. For each MG_k that violates the 2.1.3.
      2.1.4.1. Sort the utilities by profits in decreasing order in *list[N]*
      2.1.4.2. For each utility u_j in *list*
        2.1.4.2.3. For rest utilities (which MG_k has fewer profits) $\Pi_{iu_l} < \Pi_{iu_j}$, decrease their maximum capacity by x_{ij}: $X_{il} = X_{il} - x_{ij}$
      2.1.4.3. For $X_{ij} \le 0 \rightarrow X_{ij} = 0$
  2.2. Go to step 2.
3. Set market price $p = \max\{\lambda_i\}$

2) The Non-divisible case

The non-divisible case is somewhat simpler than the divisible case, since each MG must be assigned to only one utility. Similarly to the divisible case, the allocation problem can be viewed as a multidimensional MKP with the second dimension being the profits of each MG. However, as already explained each MG allocation affects the supplies of the other MGs, implying that the allocation algorithm needs to be performed multiple times until the constraints are all met. In contrast to previous subsection, the aggregator for each utility sorts MGs by profits in decreasing order. Then, the aggregator sequentially serves the largest residual demand (utility) with its next most profitable MG. This procedure is repeated until either all profitable MGs are allocated to a utility or until all demands are covered. Whilst an MG might be profitable for more than one utility (efficient to multiple utilities), however, in this policy, the MG can be allocated to only one utility. Therefore, if an MG has already been allocated, the aggregator ignores it and moves to the next most profitable MG. In this way, all utilities will have their demand met and moreover the competition among the competitive MGs will be also reduced. This process must be repeated until an equilibrium is reached so that no changes are to be made. Similarly, the market price is the maximum price that satisfies all the demands. The algorithm that solves this allocation problem is presented in Table III.

Table III Pseudocode of algorithm for non-divisible case and cost function dependent on utilities

1. Initialize list of residual demands $ResD_j=D_j$, list of unallocated MGs $UnMG = \{1,2, \ldots M\}$, allocated MGs of j-th utilities $AMG_j = \{\emptyset\}$, where $j=1,..N$ the utilities and $i=1,2,...,M$ the MGs in the market
2. Repeat
  2.1. For each demand D_j (j-th utility)
    2.1.1. Create set $S = \{AMG_j\} \cup \{UnMG\}$
    2.1.2. Calculate supplies of i-th MG, x_{ij} , and price λ_j for maximum supplies $X_{ij,max}$ [see (5)] and for $MGs \in S$ using DCA
  2.2. If the MGs allocated to each utility are the same with the

MGs that supply this utility, then go to 3
2.3. Set $ResD_j = D_j - \sum_{i \in AMG_j} x_{ij}$
2.4. For each utility u_j sort MGs by profits in decreasing order in *list*
2.5. Until either all $ResD_j$ are 0 or all profitable MGs have been allocated,
2.5.1. Obtain the utility u_j with the maximum $ResD_j$
2.5.2. Find next not allocated and most profitable MG of u_j: $MG_k \in UnMG_r$.
2.5.3. Update $AMG_{u_j} = \{AMG_{u_j}\} \cup \{MG_k\}$
2.5.4. Update list $UnMG = \{UnMG\} - \{MG_k\}$
2.5.5. go to step 2.5
2.6. Go to step 2.
3. Set market price $p = \max\{\lambda_i\}$

IV. Results

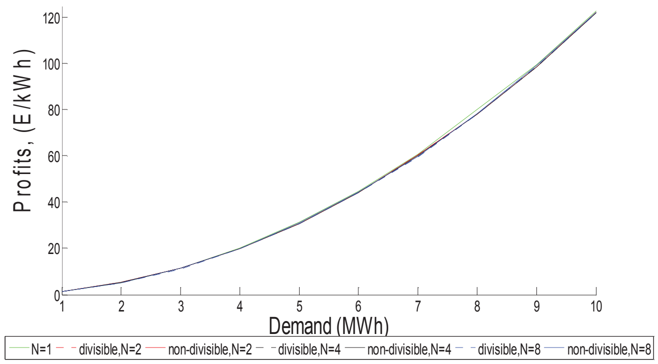

Fig. 3:Profits of MGs versus demand for different number of utilities and with cost function of MGs independent to utilities

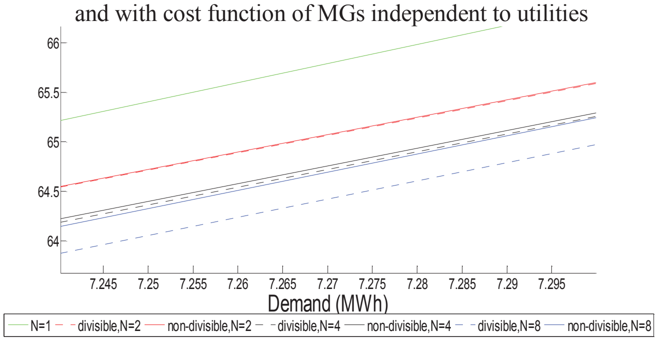

Fig. 4:Closer look of Fig.4

For our simulations, we set up a distribution network within a square of 150x150km^2 with the target area (the point which the demand is headed for) and the MGs randomly deployed within this area. The resistance between any two nodes (MGs) and the voltage line (which define b_i parameters) are set to $R_0=0.2$ ohm per km and to 230V, respectively, which are practical values in the lower level of the distribution network [11] . For simplicity purposes, we assumed that $\delta_i=0$. Typical small scale installations have capacities within the range [1kW-30kW], therefore, the capacities of MGs are assumed to be Gaussian random variable with mean 15kW. In order to evaluate realistic experiments of a day-ahead market, statistical data from Greek electricity market were used. In particular, observing the statistical data of Greek electricity market at September 2013 we see that a realistic day-ahead market includes demands ranging from 4 to 7 TW. Due to computational limitations we used 1000 MGs able to cover a smaller portion of the actual demand. Nevertheless, without any loss of the validity of our results we used the above daily demand pattern in the range [4-7]MW. The demands for different utilities are also assumed to vary with a variance of 20% from the mean demand. By using values for investment costs as is instructed in [12] for the small scale PV investments, the b_i parameters for MGs range in [0.11, 0.16]. All statistical results are averaged over a large number of runs with different random positions, capacities, a_i's and b_i's parameters.

A. *Multiple Allocation with costs independent to Utilities*

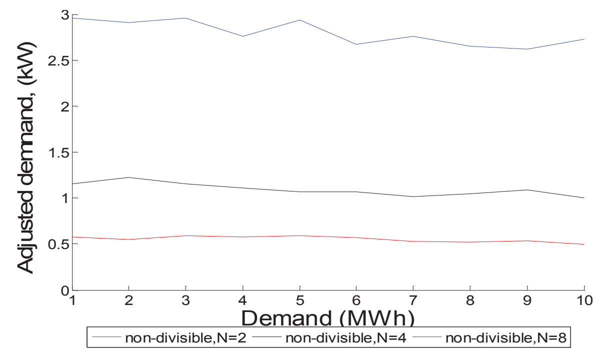

Fig. 5: Demand adjusted by the aggregator in order to precisely match the demands

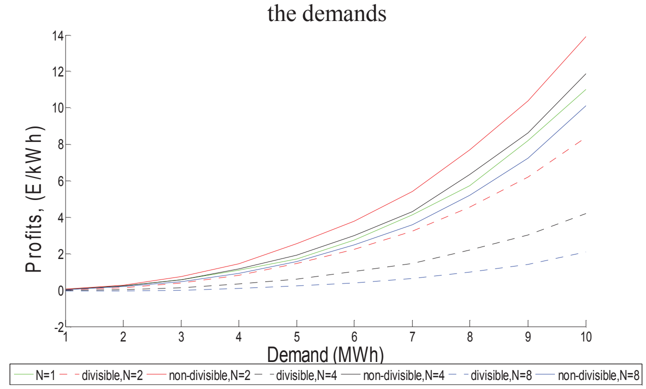

Fig. 6:Profits of MGs versus demand for different number of utilities and with cost function of MGs dependent to utilities

In Figs. 3,4 we observe the impact of the number of utilities (N) in both supply policies (divisible and non-divisible), assuming that the costs functions for producing the energy are independent of the location of the utilities to which the energy is sold (negligible transportation costs). That is, we used the same a_i but different b_i in the cost functions of MGs [see (2)]. In general, we observe that in this case, both the divisible and the non-divisibility are almost equally beneficial for the MGs (Fig. 3). This is because in the non-divisible case the cost functions of the MGs are not affected by the utilities. As a result their supply function is only dependent on the individual requested demands and the supply of the other participants. However, since those demands are many times bigger than the capacities of MGs, the profits deviate insignificantly from the divisible case. The slight superiority in the profits of the MGs in the non-divisible case can be seen in the Fig. 4, which is a closer look of Fig. 3. Interestingly we see that as the number of utilities increases, the gap among the two policies also increases. In Fig. 5, we observe the amount of the demand that was adjusted in order to precisely meet the requested demands. As expected, the entrance of new utilities in the market increases the variations in demands that the aggregator must compensate in order to perfectly match the demands.

B. *Multiple Allocation with costs dependent to Utilities*

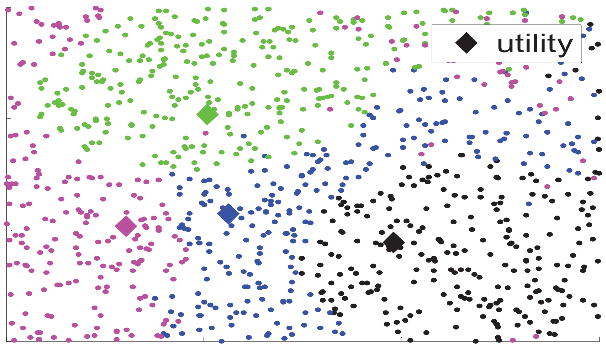

Fig. 7: MG allocation from aggregator among 4 utilities in the non-divisible case with cost functions dependent to the location of utilities

In Fig. 6 we observe the impact of the number of utilities under both supply policies, assuming that the costs functions are dependent on the location of the utilities. That is, we have same b_i's but different a_i's in the cost functions of the MGs. Since the b_i's are all equal, the increased profits of an MG for a utility means that it is closer to this utility. Therefore, in this experiment the aggregator considers only the transportation costs and naturally allocates the MGs to utilities in a geographical manner, respecting any capacity constraints (see Fig. 7). As the number of utilities increases in the examined area, both the transportation costs are reduced and the demand is split to even smaller pieces. Therefore, the profits rationally decrease with the entrance of new utilities in the market. However, it is clear that the non-divisibility case results in more benefits for the MGs than the divisible case. Interestingly, as the number of utilities increases the deviation of profits also increases between the two cases. The reason for the performance of the non-divisibility is that the effective MGs that could possibly offer their units to more than one utility are now limited to supply only one, eliminating intense competition. Side effect of this is that the utilities are also forced to turn to more expensive MGs, thus, increasing both, the price and profits of the closer to them MGs.

V. CONCLUSIONS

It is expected that numerous small MGs and many power utilities will form the scenery of the future RES electricity liberalized market. In this market aggregators will be called to play a significant role by decentralizing the electricity market and by aggregating the small quantities of energy produced by tiny MGs and making them tradable in the market. Environmental policies will pose regulation constraints on each utility that must be fulfilled, if monetary penalties are to be avoided. In order to face this problem each aggregator (who might also be a RES local market operator) should form algorithms that allow to distribute the supply among the utilities in order to meet their demand of RES units. We considered two supply policies under which the allocation of the production of many microgrids into multiple utilities will be performed. In the first, divisible policy, the producers are assumed to be able to split their supply into smaller partitions and distribute them to more than one utility. This case includes the subcase where one utility exists in the market and the price is determined from supplying to it the aggregated demand. In the second non-divisible policy, the microgrids are not allowed to split their supply and an algorithm that sees the allocation as a knapsack problem is proposed to perfectly match the individual demands. We also considered two cases for the cost functions of the microgrids. In the first case, the producers supply different utilities in the same manner (same cost functions per utility), while in the second case transportation costs are also involved. Different utilities may entail different transportation costs and, thus, different cost functions may be entailed for each (microgrid, utility) pair. In both cases, the algorithms we implemented verify that the non-divisible policy is more profitable for microgrids, even though for the first case of cost functions the differences are almost negligible. Moreover we observed that the increase of the number of utilities in the market increases the gap in profits between the two policies. In contrast, the divisible case is more profitable for utilities, as expected, since the more effective MGs are allowed to supply more than one utility, decreasing the overall cost.

ACKNOWLEDGMENT

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