Integration of a PV energy balancing and trading mechanism in a microgrid

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ABSTRACT

In this work we address the distribution of PV power generated in a microgrid connected to the main grid. Following the idea of a local energy community, the new goal instead of self-consumption maximization is to enable the local trade between PV producers and neighbored consumers in the microgrid. By using a simple "many-to-many" lexicographic allocation and balancing algorithm between producers and consumers, we analyze the resulting price at the consumer. To control flexible loads in a high PV penetration scenario, we propose instead of price information, the use of PV energy surplus. Numerical results are given for an EV charging scenario.

INTRODUCTION

The planning and investment in rooftop PV panels has been guided until now by the self-consumption of the PV owner. Recently, projects are conducted to allocate the PV power not only to the various inhabitants of a building, but also to develop platforms for local energy trading, for instance with the neighbors across the street. The new approaches are published under various names such as peer-to-peer (P2P) energy trading [5], district or community microgrids, or transactive energy systems [4],[11]. The latter approach tries to apply mechanisms used in the wholesale energy market, such as auctions and locational marginal prices, down to the community and microgrid level.

Early projects such as Brooklyn Microgrid (TransactiveGrid) [2], Share and charge [3], Picio (Open Utility) [10], or Tal.Markt [12] have shown that micro-balancing algorithms running decentrally could be used for peer to peer trading and sharing applications. The main challenges for the creation of a neighborhood energy market have been and still remain the technology for automatic balancing and settlement, the consideration of DSO infrastructure costs, cyber-security aspects, and the adaptation of the legal framework to allow local trading.

The contributions of this work are twofold: first, we describe a many-to-many energy allocation and pricing algorithm for trading renewable energy between producers and consumers in a community grid, and second, we use this allocation to dispatch flexible loads such as EV charging tasks.

Microgrid control environment

A neighborhood consisting of PV energy producers and consumers can be modelled as a microgrid. Without making use of its islanding functionality, the considered microgrid has the capability to control the loads of individual buildings, including the distributed energy sources (DER) such as PV generation, battery storage, etc. The hierarchical control system consists of customer energy management systems (CEMS) that aggregate different local loads and provide the microgrid controller (MG) load forecasts for the next hours and aggregated flexibility information. The MGC computes setpoints for each CEMS. In case of peak loads at point of common coupling (PCC), the setpoints indicate, which CEMS should reduce their loads, see [6], [7], [8].

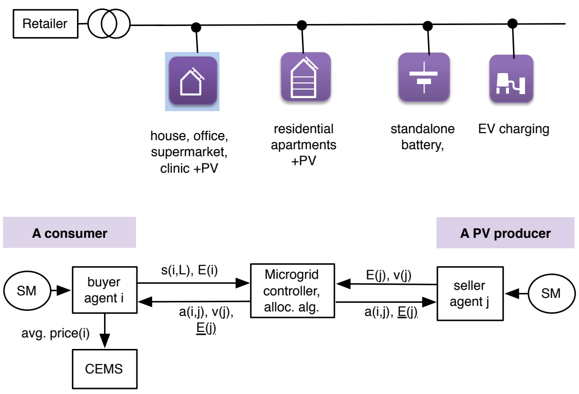

Figure 1: Community grid system overview architecture

Figure 1 shows a feeder in a low voltage grid that connects PV producers, consumers and various assets. The market is schematically illustrated by connecting selling and buying agents to a local (microgrid) controller, where the energy allocation and the prices are computed. Smart meters (SM) provide measured generation and consumption data, whereas the agents decide on the trade strategy, see below. Finally, price-based demand response schemes can be triggered at the customer level.

PRICING CONCEPT AND SYSTEM ARCHITECTURE

In this section we propose a bilateral trade mechanism, which is based on price discrimination (pay-as-bid), meaning that the energy price requested by a PV-producer is actually paid by consumers. The proposed energy supply model allows each customer to specify up to four preferred PV producers in an individual preference order. The fourth provider is always the retailer (R), usually more expensive than the local PV producers, but always capable to supply the outstanding demand. Similarly, the retailer buys all the excessive generated PV energy at a low feed-in tariff. The consumer strategy is to update the preference order list, whenever the price of the energy mix can be reduced. This is done manually by the consumer, or computed by a computer agent [8]. If the matched producer and the consumer are not co-located (i.e. not located in the same building), then additional fees will be charged by the DSO for the use of the grid infrastructure. The application of nodal pricing [9] in which prices reflect electrical grid constraints (like implemented in the US electricity markets for higher grid levels), would require the full network topology for solving power flow equations. We try to avoid this complexity because in practice low voltage grid topologies are either not well documented or not available at all. In addition, we assume that microgrid congestion and high reverse flow situations can be handled in our Demand Side Management (DSM) architecture via setpoints from the central controller towards the CEMS, with the effect of reducing the number of voltage events considerably [6][13]. Therefore, we propose to approximate the grid costs with the socialized tariff used currently for private customers. The architecture in Figure 1 consists of a microgrid controller that hosts the allocation algorithm described below, and several customer energy management systems (CEMS) using the computed energy price as a basis to control the flexible loads (e.g. charging of electric vehicles, charging/discharging the home battery, air conditioning systems). The consumption and local generation data needed by the algorithm is provided by smart meters. The allocation scheme, described in detail in the Appendix, works as in what follows: if the first producer on the preference list of a consumer cannot provide all the demand, the second producer on the list will provide a share of its power equally divided between those consumers that are selected in the second level, and so on. Finally, the retailer provides the rest. We show in [8] that in case of non-zero infrastructure costs, the allocation scheme outperforms the double auction with respect to the total welfare.

Marginal prices

The proposed allocation scheme leads to a bilateral, pay-as-bid agreement between PV producer and consumer. In the example in Figure 2 the customer's demand uses already the third PV producer, as it exceeds its allocated share from first and the second preferred PV producer. Note that, other than in the double auction, the producers are ordered according to the consumer preferences and not to increasing ask price. The marginal price, defined as the price for the next consumed kWh, is in our example the selling price of the 3rd PV producer, as long as the additional load does not exceed the "surplus" of PV energy. Otherwise, the price becomes the expensive retailer price, and the dispatch of a flexible load during that time brings no cost advantage. Therefore, we will study the effect of energy surplus on demand response decisions.

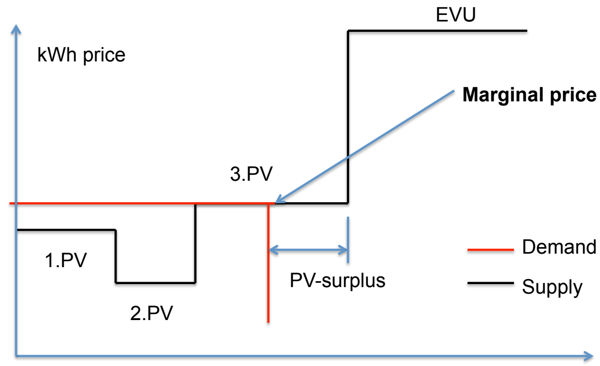

Figure 2: Marginal price example

Notation	Description
$j \in P$	set of PV producers
$i \in C$	set of consumers
R	retailer (utility)
E_j^p	kWh units of producer j (per sampling time unit)
E_i^c	energy required by consumer i
v_j	selling price of producer j [ct/kWh]
L	L=0,1,2 preference order (level) for producer selection
s_{iL}	i's prefered producer list, $s_{i3} = R$
a_{ij}	energy bought by i from $j \in P \cup \{R\}$
$\underline{E}_j$	energy sold by producer j to R
loc_{ij}	one, if producer j is co-located with consumer i, zero else

Table 1: Notation summary

Assume the preferred producer list of consumer *i* is s_{iL}, $L=0,1,2$ and the amount bought from producer *j* is a_{ij}. The total surplus (that consumer i must however share with other consumers) is the sum of not-sold energy

$$E_i^s = \sum_{j \in [s_{i0}, s_{i1}, s_{i2}]} \underline{E}_j \qquad (1)$$

In the next section we will use the surplus of renewable, low cost energy to determine the best interval to dispatch an EV charging load.

APPLICATION TO EV CHARGING

The optimized usage of renewable energy can be considered in various scenarios of electric vehicle charging: private charging stations, sharing of private charging stations, public charging stations for a parking lot, etc. In this work we focus on multiple private charging stations, each one being attached to a household and controlled by the local CEMS. In general, the EV availability interval for charging could be known by the system some time in advance. The longer this time, the more accurate the charging schedule becomes. Another input parameter is the amount of energy to be charged. In contrast to previous models (see [1] for a survey), the charging power is a parameter, but it remains constant during the charging period. The varying power charging model is theoretically better, however it is not supported by the industry standards [1]. Moreover, the charging task should not be interrupted.

In a scenario with high renewable penetration, the objective is to maximize the share of renewable energy in the consumption. Although marginal prices signalize the availability of renewable energy, more information is provided by the PV surplus, which is however shared by several consumers. Therefore we will plan the charging cycles in times with maximum renewable energy surplus.

Denote the planning horizon consisting of the periods $j=1..N$. Given the charging demand, we can compute dur, the duration in periods for charging this demand with the given charging rate. As the planning horizon window rolls forward and overlaps with the car availability period, we can identify all the possible start times $t_s(j)$ for a continuous charging operation and the surplus s_j at time j. The best start time is

$$\arg\max_j \sum_{j \in [t_s(j), t_s(j)+dur]} s_j \tag{2}$$

Optimality cannot be guaranteed because the other CEMS controllers decide independently over the begin of the charging cycle using only their view of the renewable surplus according to definition (1). In case the system is overloaded (the surplus is zero and the total proposed load of the microgrid exceeds the nominal power limit), the decision upon the start time of charging activities is coordinated by the microgrid controller using the power setpoints [15].

NUMERICAL RESULTS

For microgrid simulation we use a discrete time simulator that consists of a microgrid controller and an arbitrary number of CEMS controllers, all running in the same java virtual machine. The high PV penetration scenario is simulated using four houses with large PV panels that produce 40kWp each. In this example we assume that the power connections of these houses are dimensioned to support these reverse power flows. Seven consumers are configured as residential houses and small offices and provide a standard load profile and in addition consumption due to air conditioning (summer day simulation). The prosumers sell their PV power with prices uniformly distributed between 10 ct/kWh and 12 ct/kWh, the DSO charges 2ct/kWh for the infrastructure usage (this price is set under the assumption that reduced grid fees apply and no taxes and other fees have to be paid), and the retailer price is for simplicity reasons kept constant at 20ct/kWh. The allocation and settlement is performed every 15 minutes. The baseline scenario runs from 7am to 7pm and is compared with a scenario in which each consumer adds a charging EV load. The availability of each EV for charging is 7.5 hours, starting at each full hour between 10am and 3pm. Each car charges in total 12kWh at a rate of 3.7kW, the resulting charging duration being over 3 hours.

In Figure 3 we show the power supplied by the retailer with and without the charging tasks, as well as the contributions of the PV producers. Note that all the PV power results from local trade, as the self-consumption has been already subtracted from the PV production. Depending on the time of the day, the use of PV power increases to the maximum in case charging loads are added; however, also the retailer contribution increases as the surplus for most users becomes zero.

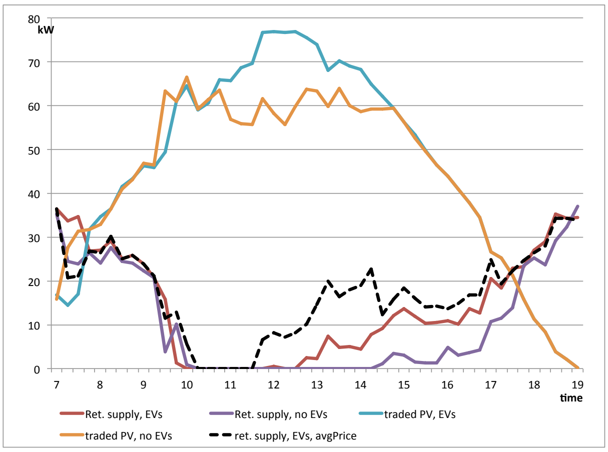

Figure 3: Retailer supply, PV traded power with and without charging tasks

For comparison purposes we calculate the charging start using the average kWh price over the four providers. The dotted curve in Figure 3 illustrates the energy supplied by the retailer, which is higher than the one using PV surplus optimization, in the same simulation conditions. The comparison shows as expected that the PV surplus criterion performs better than price information. The reason is that the surplus indicates the potential of adding more load without a price increase.

from c_i	to p_j	payment[ct]	ct/kWh	kWh
4	2	20	11,33	1,79
5	2	20	11,33	1,79
6	3	21	11,56	1,79
7	3	21	11,56	1,79
8	1	64	10,39	6,19
8	2	15	11,33	1,31
8	3	117	11,56	10,10
8	DSO	35	2,00	17,60
9	1	64	10,39	6,19
9	2	15	11,33	1,31
9	0	116	11,44	10,10
9	DSO	35	2,00	17,60
10	1	64	10,39	6,19
10	2	15	11,33	1,31
10	3	117	11,56	10,10
10	DSO	35	2,00	17,60
RET	0	10	8,00	1,19
RET	3	63	8,00	7,88

Table 2: Transactions created in a trading period

The allocation and pricing algorithm creates periodical transactions that can be used for payment. Table 2 is an example of the transactions created during a certain 15 minutes period. The consumers 4 to 7 each use the energy of one (co-located) PV producer, the consumers 8, 9 and 10 are supplied each by three PV producers and pay grid costs as well, finally the retailer pays the feed-in tariff to producers 0 and 3.

CONCLUDING REMARKS

In this work we analyze a scenario with high penetration of PV production, which could be the result of local trading and increased profitability of renewable energy installations. We present an energy allocation and pricing scheme in which grid costs are also considered. Looking at the marginal price the consumer pays, we show that the usual price discrimination control decision for demand response can be improved using the renewable energy surplus. We applied these considerations for home EV charging, such that the charging period makes maximal use of renewable energy.
As a potential way for realization of the payment mechanism, the blockchain technology could be used; it implements immutable transactions, which are visible for all participants. Future work will evaluate several designs for including blockchains into the architecture with special focus on the security and privacy aspects.

ACKNOWLEDGEMENTS

This work has been performed within ”Sonnwende+” (project ID 861621), a project of the Austrian RTD program ”City of Tomorrow”. The program was created by the Austrian Federal Ministry of Transport, Innovation and Technology, and is run by the FFG, AWS and OEGUT Austrian research management firms.

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Appendix

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Data: i ∈ C, j ∈ P, L = 0, 1, 2, s_iL, E^c_i, E^p_j
Result: a_ij
initialization;
e^p_j = E^p_j  e^c_i = E^c_i
for level L=0, 1, 2 do
    for j ∈ P do
        demand from producer j: e_j = Σ_{k∈C} e^c_k | s_kL = j
        for e_j > 0 do
            α_j = e^p_j / e_j
            if α_j < 1 then
                for i ∈ C do
                    a_ij = α_j e^p_j; e^c_i = (1 − α_j) e^c_i; new
                    e^p_j = 0;
                end
            else
                for i ∈ C do
                    a_ij = e^c_i; e^c_i = 0; e^p_j = e^p_j − e_j;
                end
            end
        end
    end
end
E bought by retailer:
for i ∈ C do
    a_{i,|P|+1} = e^c_i; e^c_i = 0;
end
E sold to retailer
for j ∈ P do
    e^{feedIn}_j = e^p_j
end
```

Algorithm 1: Lexicographic power allocation