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Smart Grids for Optimised Utilisation of Renewable Energy Supply

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Abstract

Future energy systems will increasingly rely on distributed and renewable energy sources (RES). Electrical feed-in of photovoltaic (PV) power plants and wind energy converters (WEC may vary greatly, the supply of electrical power from RES and the demand for electrical power are not per se matching. and in addition, with a growing share of generation capacity especially in distribution grids, the top-down paradigm of electricity distribution is gradually replaced by a bottom-up power supply. This altogether leads to new problems regarding a safe and reliable operation of power grids. In order to address these challenges, the notion of Smart Grids has been introduced. In this context, autonomous agents and the concept of self-organising systems are key elements in order to intelligently use the inherent flexibilities of distributed generators, power storage systems and power consumers. Our research goal is to optimise the local utilisation of RES feed-in in a given power grid by intelligently integrating both supply and demand management measures and with special respect to the electrical infrastructure. In this paper first we show how an intelligent load management system for battery charging/discharging of electrical vehicles EVs can increase the locally used share of supply from PV systems in a low voltage grid. For a reliable demand side management of large sets of appliances dynamic clustering is necessary. We show how control of such clusters can affect load peaks in distribution grids. Additionally we give a short overview how we are going to expand an attempt of self-organised clusters of units to a virtual control centre for a dynamic virtual power plant.

1. Supply-demand-matching considering renewably energy sources

Future energy systems will increasingly rely on distributed and renewable energy sources (RES). In 2030, between 50% (BMWi 2010) and 67% (BMU 2012) of the gross electricity demand of Germany are expected to be covered by electric feed-in from RES; in 2050, this share is expected to grow up to 85% (BMU 2012). In course of this politically driven evolution of an energy system, new challenges regarding the successful and sustainable integration of RES both into the power grid and into energy markets have to be addressed: As photovoltaic (PV) power plants and wind energy converters (WEC) rely on solar radiation and wind, respectively, their electrical feed-in may vary greatly and unforeseen in small amounts of time (stochastic fluctuation of RES feed-in). In addition, the supply of electrical power from RES and the demand for electrical power are not per se matching, that is there are times of high electrical feed-in and low power demand, vice versa. Even with today’s comparatively low share of RES, these situations may yield negative electricity prices at the European Energy Exchange (EEX) (Wissing 2012) due to the (short-term) surplus of power generation. Regarding the electrical infrastructure, the integration of RES increases the strain on power grid assets (e.g. power transformers) as today’s power grids where historically designed for a top-down power transmission and distribution. With a growing share of generation capacity especially in distribution grids, the top-down paradigm is gradually replaced by a bottom-up power supply, leading to new problems regarding a safe and reliable operation of power grids (e.g. voltage control and power grid protection measures).

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In order to address these challenges, the notion of Smart Grids has been introduced. The European Technology Platform (ETP) defines Smart Grids as “electricity networks that can intelligently integrate the behaviour and actions of all users connected to it - generators, consumers and those that do both – in order to efficiently deliver sustainable, economic and secure electricity supplies” (EU ETP 2010). Intelligent behaviour is thus a key element of Smart Grids and a prerequisite for an optimized utilisation of renewable energy supply. Taking the outlined challenges into account, our research goal is to optimise the local utilisation of RES feed-in in a given power grid by intelligently integrating both supply and demand management measures and with special respect to the electrical infrastructure. We aim to match supply and demand of electrical power on a local scale, taking grid load into account. In this context, autonomous agents and the concept of self-organising systems are key elements in order to intelligently use the inherent flexibilities of distributed generators, power storage systems and power consumers.

In section 2 of this paper we show how an intelligent load management system for battery charging/discharging of electrical vehicles (EVs) can increase the locally used share of supply from PV systems in a low voltage grid. Additionally, this load shifting method allows reducing the average load at the local transformer station significantly. Integration of large sets of small appliances into load management raises questions of predictable behaviour of these devices as well as scaling problems for control algorithms. For a reliable demand side management of large sets of appliances clustering is necessary which is outlined in section 3. Section 4 of this paper gives a short overview how we are going to expand an attempt of self-organised clusters of units to a virtual control centre for dynamic virtual power plants. This virtual control centre includes distributed methods for schedule optimization as well as rescheduling of units.

2. Increasing local utilisation of supply from PV systems using batteries of EVs

In this section we show how a (central) intelligent control method for smart charging of electric vehicles (EVs) can increase the local use of PV supply in a low voltage (LV) power grid. Additionally, we show that grid constraints – i.e. the strain on local grid assets such as power transformers – can implicitly be taken into account by such a control method (Tröschel et al 2011).

A major challenge regarding smart charging of EVs is simultaneity. Consider the following thought experiment: In a small urban low-voltage (LV) grid comprising 70 (high-income) households, 20 battery electric vehicles (EVs) are located. The local power transformer has been laid-out for a maximum load of 200kVA, which is quite comfortable regarding the households’ yearly peak load of about 120kW. Each EV has a maximum storage capacity of 30kWh and a maximum charging power of 10kW (three-phase connection point). The EVs are mostly used for commuting, that is on work-day evenings they are all returned more or less at the same time to their charging station. Uncontrolled charging – starting to charge an EV’s battery as soon as it is connected to the charging station – can then result in a massive strain on the local power infrastructure: When all 20 EVs charge at the same time (i.e., with high simultaneity) up to 200kW charging power is needed in addition to the power demand of the 70 households. As the transformer has been designed to allow a maximum load of only 200kVA, the resulting thermal strain may lead to an increased aging or even damaging of this expensive asset.

With this worst-case scenario in mind, we developed a smart charging algorithm with two major design goals: 1) reduce the simultaneity of the charging process, and 2) maximise the local utilisation of electric feed-in from PV systems. Thus, not only the strain on power grid assets should be reduced, but the EVs should also be charged with as much renewable energy as possible. The basic idea is as follows: We introduce a central management server at the substation level, such that the charging process in an LV grid is being managed by a single optimising instance. As soon as the EV has connected to the charging station, four parameters are transmitted: The expected parking time (provided by the user), the current state of the battery, and a charging goal (e.g. 85 %) with some flexibility (e.g. ± 15 %). The central server's objective is to generate plans in such a way, that the sum of all plans approximate a given load curve while each individual plan reaches the charging goal within the parking time available. Thus, the EVs' users' needs are taken into account, which is a prerequisite for acceptance of smart charging concepts (Schlager et al 2011, Weider et al 2011). The optimisation process comprises the following three phases (for a more in-depth discussion please refer to (Vornberger et al 2011)):

1. Minimum charging: In phase one, the batteries are charged up to a minimum state of charge (SOC), e.g. 20% of their maximum capacity. This ensures a minimum mobility guarantee for the users.
2. Distributed charging: In phase two, charging is distributed over a number of charging slots (e.g. 15-minute time slots over one day) in order to reduce simultaneity. The target load curve – the desirable resulting power demand at substation level – is taken into consideration to find 'good' slots. For that purpose, the numerical difference between the currently expected load (the sum of all charging loads) and the target load is calculated for each time slot. Based on this difference, a charging probability is calculated for each time slot, such that slots with a higher difference will be assigned a higher charging probability. Based on these probabilities, a random combination of charging slots is chosen. This ensures that charging will more likely occur in times where extra load is required.
3. Additional charging / discharging: Provided the EVs support discharging, that is acting as a generator from the grid's point of view, in the third phase additional time slots for charging and discharging are selected in order to minimise the difference of expected load and target load.

For the evaluation of our approach, we relied on the Smart Grid simulation framework mosaik (Schütte 2011). Based on data from a local distribution system operator, we modelled an LV grid comprising 71 private households and conducted several simulation studies – each over the course of one simulated year – with varying shares of PV systems and EVs. **Table 1** lists the setup for the results discussed below:

Table 1: Simulation study setup

Influencing factor	**Value**
EV share	50% of the households have an EV
Installed PV peak power	160kWp, shared amongst 50 plants with 3,2 kWp each
Grid type	Rural grid, EWE Netz GmbH
Charging strategies	Uncontrolled, controlled, vehicle-to-grid (V2G)
Battery capacity	31 kWh
Charging/Discharging power	≤ 3,7 kW single-phase, ≤11 kW three-phases

Using this setting, we compared three different charging strategies regarding their performance when trying to balance supply (from local PV systems) and demand (from households and charging EVs):

- Uncontrolled charging: EVs are charged as soon as they are connected to their charging point until their SOC reaches 100% (or until they are disconnected by the user).
- Controlled charging: EVs are charged relying on the central smart charging strategy discussed above. However, EVs do not have the capability to feed power back to the grid.
- Vehicle-to-grid (V2G): EVs are charge relying on the central smart charging strategy discussed above and have the capability to feed power back to the grid.

Local utilisation of supply from PV systems (cf. Figure 1):

Regarding the utilisation of electric feed-in from local PV systems, the vehicle-to-grid approach yielded the best results. Due to the EVs' capability to feed electrical power back to the grid in times of high demand, a very large share of the PV feed-in was used to satisfy the demand of both households and charging of (other) EVs. The electrical power exported to superordinate grid levels was thus minimised. It is also noteworthy that the controlled charging approach wasn't able to significantly improve the local utilisation of PV feed-in compared to uncontrolled charging. This somewhat unexpected effect results from the fact that the EVs' batteries were in this case only discharged when driving. Thus, the total annual energy throughput was significantly lower than in the case of the vehicle-to-grid approach.

Strain on local power assets:

Regarding the strain on the LV grid's power transformer, also the vehicle-to-grid approach performed best: Almost half of the (simulated) time, the transformer load was close to zero - that is supply and demand were actually balanced (cf. **Figure 2**). Additionally, the peak loads were significantly reduced compared to the other charging approaches (and even compared to the load without EV). Again, controlled charging only improved the situation little.

In summary, we were able to demonstrate that an intelligent usage of flexibilities in LV power grids (here: smart charging of the EVs' batteries) is able to match supply and demand locally, thus improving the utilisation of renewable energy and simultaneously reducing the strain on local power assets such as power transformers. Due to the centralised optimisation and the high computational complexity, however, this approach is only feasible for very limited numbers of systems that are to be controlled.

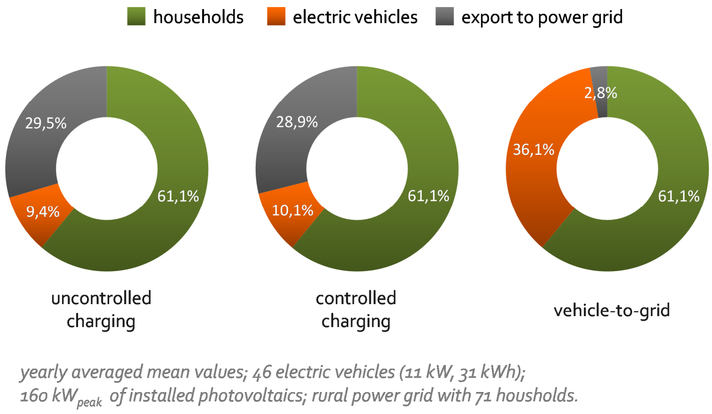

Figure 1: Results regarding the local utilisation of PV feed-in

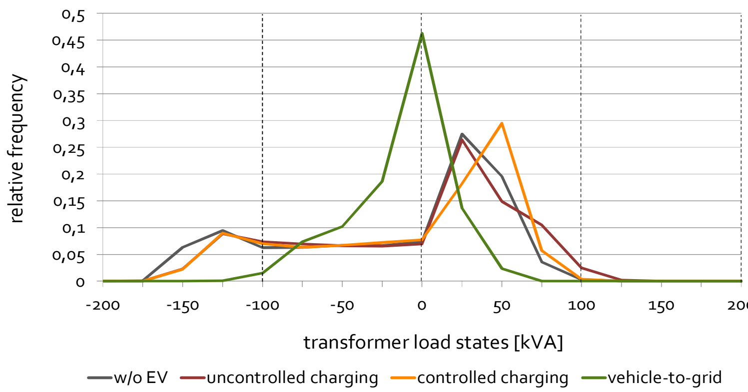

Figure 2: Probability density function of the local power transformer's load

3. Self-organised clustering of small appliances for load balancing

In this section we demonstrate how decentralised organized clusters of devices, e.g. household appliances or EVs as well, can be used for control purposes, e.g. reduction of load spread in a medium voltage grid. This method especially aims at improved scalability – a major weakness of centralised approaches such as the one discussed in the previous section – and is explained in more detail in (Lünsdorf 2012). We explain this approach in a bottom-up manner.

An essential technical prerequisite for this approach is a hardware controller embedded into the controllable devices, offering a two-way communication channel to some external control agent. The controller needs to be able to intervene in the operation mode of its device and trigger a temporal change in consumption. An example for such an intervention is shown in **Figure 3**. The user has activated his washing machine at 12 o'clock but delayed the start by 3 hours and allowed the external control agent to override his setting and start the washing machine at any time in this timeframe. The override is performed by sending a signal (in the example in **Figure 3** this happens directly at 12 o'clock) to the device's controller.

The premature start of the washing machine causes a temporal change in power consumption relative to the normal operation mode: an increased consumption is followed by a later decrease in consumption. For friges a similar control method has been discussed in (Stadler et al 2009).

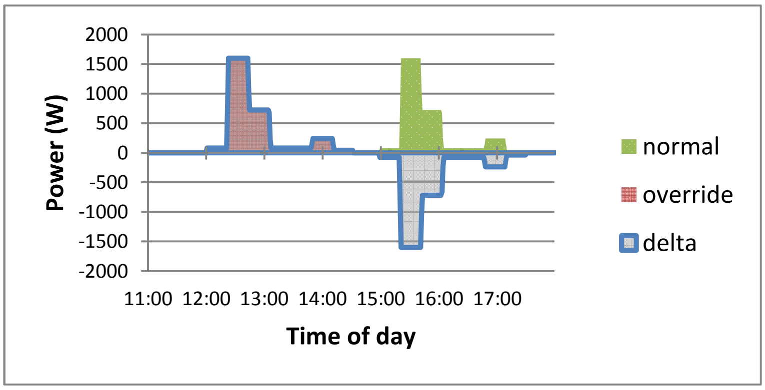

Figure 3: Load curve of a controlled device

The effect of these possible overrides in power consumption of a device need to be predicted in the form of a time-series of power demand values, called a power schedule. In general, such a power schedule is a series of values for (active) power consumption within a given time frame based on a resolution of e.g. a quarter of an hour, where power demand (or conversely supply) is fixed within these slots.

For most appliances such as dish washers or washing machines the expected effects of override signals differ over the course of a day. The forced start of a washing machine as depicted in the example above is only possible if the user has activated the device, and almost nobody starts a washing machine at night. To overcome this problem, a day is sampled into time slots and the predictions are calculated individually for each time slot. With a resolution of 15 minutes this amounts to 96 predictions (power schedules) for a day. The effects of overrides are subject to uncertainty and vary significantly between device types. Because of these uncertainties (like activation time and delay in this example), predictions are usually subject to substantial errors which can be expressed by time-series of variances for each time slot.

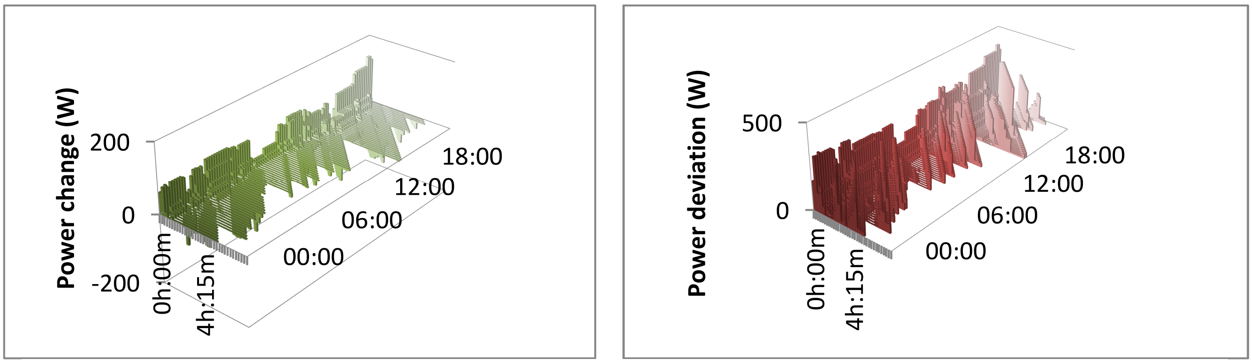

Figure 4: Prediction of change in power consumption (left) and estimated prediction error (right) for a washing machine

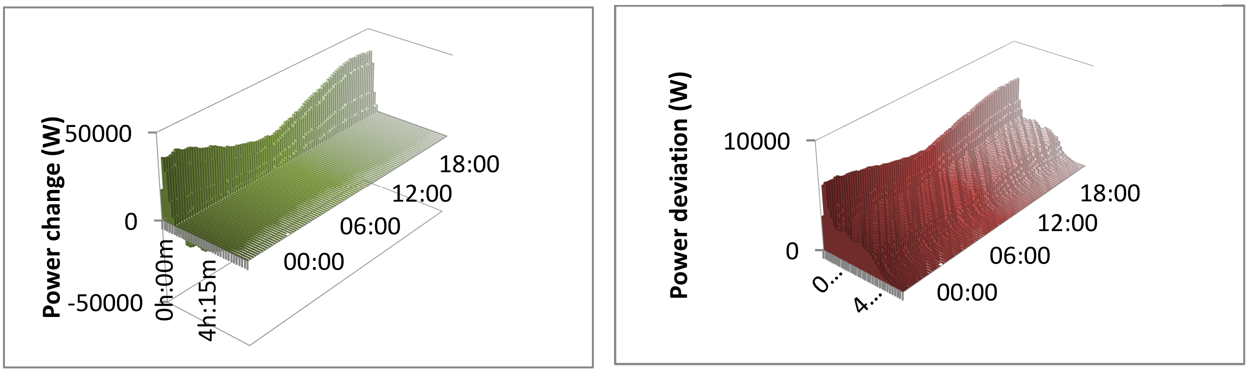

Figure 5: Prediction of change in power consumption (left) and estimated prediction error (right) for 500 washing machines

The controller needs to calculate the expected effects of operation mode overrides for every time slot as well as the estimated prediction errors of these effects. This is based on a simple statistical model of observations of the devices' usage in the past. **Figure 4** shows the predicted effects of operation mode overrides for a washing machine in 96 time-series on the left hand side. The right hand side shows the expected error of this prediction.
This unreliability of effects of controlling a single device motivates partitioning of devices into clusters. By controlling all devices in a cluster at once, the weak law of large numbers can be exploited (Georgii 2004). Applied to a simultaneous operation mode override this means that the deviation to the expected change eventually converges to zero if the cluster size becomes big enough. Under the assumption that the effects of overrides are uncorrelated[3], it is even possible to calculate the error of grouped overrides simply by summing up the individual variances. The effect of the weak law of large numbers is shown in **Figure 5**. The left hand side is showing the predicted power change as in **Figure 4** but this time for a cluster of 500 washing machines. In comparison to **Figure 4** the error rate has dropped by an order of magnitude.

The partitioning of a set of devices into device clusters (i.e. subsets) is subject to several soft-constraints. Devices should only be added to a cluster if the relative standard deviation of the consumption change does not fall below a given threshold; this ensures clusters not becoming too big – the control agent needs several independent clusters for its purposes. Furthermore the effect of overrides should not compensate each other and have roughly the same duration. Finding a good partitioning of devices is an NP-hard problem also known as Coalition Structure Generation (CSG) (Michalak et al 2010).

Prediction updates are pushed autonomously and irregularly from the device controllers into the system. The system that implements the partitioning needs to be able to adapt to these continuous updates. Furthermore, spatial proximity (w.r.t. the power grid) must be considered too. Clusters should be formed containing devices from neighbouring low power grids to support local demand-supply matching (cf. the discussion regarding electric vehicles in Section 1). Apart from consisting of an arbitrary amount of actors, self-organising systems feature the ability to adapt to changes in the environment. This makes a self-organising system a perfect fit for partitioning devices into clusters. Each local substation is associated with an agent in the self-organising system that optimizes clusters in its vicinity (e.g. neighbouring LV grids). It is not feasible to search for an absolutely optimal partitioning as the predictions may be updated at any time. Instead the agents employ a heuristic to compute 'good' clusters. In summary, the self-organising system outlined in (Lünsdorf 2012) is continuously improving the partitioning of devices and is forming clusters which respond reliably (e.g. within given error-bounds) to external control signals. Based on such a partitioning into clusters and their expected reaction to control signals, an external control agent, e.g. situated at a utility, can compute schedules of control signals to control the power consumption of devices in these clusters.

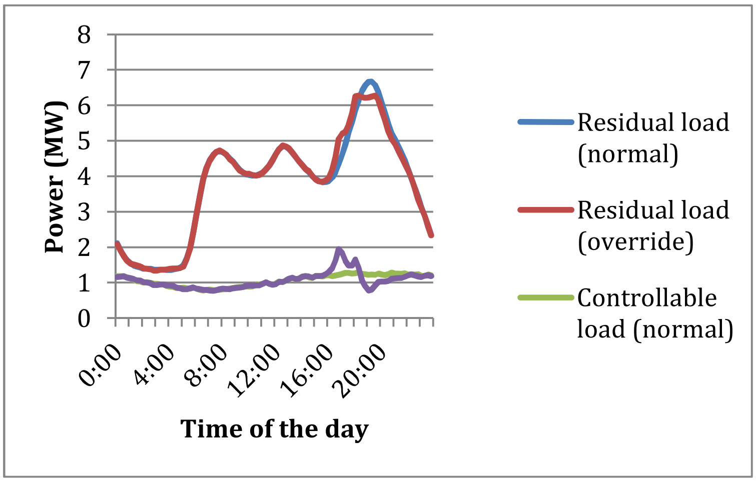

Figure 6: Power load curve of a simulated urban settlement with controllable loads

[3] This assumption doesn't hold for household appliances sometimes. An earlier start of a washing machine for example may cause the user to also activate the tumble dryer earlier. However this occasional correlation is neglected in this paper.

An example examined in a simulation study deals with the load spread reduction (max. difference in load reduced by local supply) of a small urban settlement. The scenario consists of about 35.000 household devices (refrigerator, freezers, washing machines, tumble dryers, dishwashers, heat pumps and charger stations for electric vehicles) in the year 2020. The distribution and parameterisation of the devices is based on the SmartA study (Stamminger et al 2012). A week in March has been examined in the scenario, from which **Figure 6** excerpts the power load curves for a working day. Two simulation runs were conducted. No overrides of loads were issued in the first run to simulate the normal consumption. This data is used as a reference for the second run, where overrides were scheduled to reduce the load spread. While it was not possible to increase the minimum load in the early morning hours[4], the peak load could be reduced by about 6% during work days and by 4% during the weekend (5.74% on average). This evaluation shows that it is possible to reliably control large sets of devices for load shifting using decentralised and self-organising clustering. In the outlined use-case this technique allowed to shift 1.2MWh on average per day, thus exploiting the inherent flexibility of widely used (small) power consumers in order to shift power consumption to time slots with high feed-in from renewable and distributed energy systems.

4. Market-oriented dynamic virtual power plants

In the near future – in Germany at the latest after expiration of the renewable energy act (EEG) – RES will have to offer their power at an energy market. While it is an interesting research problem how products at future energy markets will be structured, it is unquestionable that the power supply from RES has to be refined to fulfil requirements of high reliability of supply within an agreed schedule for several hours or days. Thus, small suppliers like PV systems or wind turbines have to cooperate within virtual power plants (VPPs) to (i) compensate fluctuation in the supply of single energy converters, and (ii) to exceed market entry barriers regarding the minimum power supply to be offered in a time frame[5]. Such a VPP (Bitsch et al 2002) might consist of several RES combined with controllable power plants like CHPs, battery storage systems, as well as controllable loads like heat pumps offering flexibilities for the control of the VPP. Basically also a cluster of flexible loads, e.g. appliances or EVs, can act as a VPP offering balancing power.

In the recent past, several concepts for 'static' VPPs (e.g. Mackensen et al. 2008) were examined where the participating units – usually belonging to a single owner – are fixed and control is centralised. In our research cluster Smart Nord[6] (Sonnenschein et al. 2012) we are going to expand these static concepts by methods for dynamical aggregation of units targeting a common power product represented by a power schedule. These dynamical VPPs – called clusters – cooperate only temporarily referring both to the actual situation at the market and to the prognosis of the expected feed-in from the participating units. As a consequence, decentralised control methods are required to allow clusters to be configured independently of fixed control units. For a dynamical VPP, currently four control methods that together form its virtual control unit are being developed. In the following subsections we give a very short outline of these methods:

a) Self-organising methods for the aggregation of units (RES, controllable plants, storage systems, controllable loads) to clusters (dynamical VPPs) similar to the approach mentioned in section 3. These clusters allow RES in combination with more flexible units to bid at the market.
b) A method for the efficient representation of flexibilities, i.e. sets of possible power schedules of single units for a given time frame. This representation is needed for distributed methods to plan schedules of the controllable (i.e. flexible) units within a cluster.

[4] The load minimum spans several hours and most of the devices are not active in this timeframe.

[5] Participation at the European Energy Exchange (EEX) currently requires the provision of at least 100kW electrical power.

[6] The research cluster Smart Nord is funded by the Ministry for Science and Culture Lower Saxony (MWK) through the „Niedersächsisches VW-Vorab“ (grant ZN 2764).

c) Distributed optimisation methods for generating power schedules for all units in a given cluster with respect to a power product that has been successfully traded at an energy market. This task is similar to unit commitment in the present power supply – a specific centralized scheduling method for charging/discharging of a cluster of EVs has been presented in section 2.

d) Distributed methods for rescheduling units in a cluster in case of events such as deviations from the prognosis of the feed-in from participating RES or the (unexpected) outage of a unit.

These four methods are combined in a multi-agent system where each unit is represented by its agent. In order to support methods of self-organisation, these agents are equally ranked, i.e. there are no specific coordinators and no a priori given hierarchy in the multi-agent system.

a) Self-organising clusters of units

Units can be clustered regarding technical, economical, strategic as well as dependability related criteria. In addition to economic aspects of individual units, knowledge from previously successful cluster compositions, reputation of potential partners, and reliability regarding the delivery of an offered product, particularly grid aspects have to be respected in cluster formation. So, cluster formation consists of four tasks (Beer et al. 2011):

i. An initiating agent, e.g. representing a large PV system, decides for a marketable power product that could be offered by a cluster. Its decision depends on its own possible power schedule resp. prognosis that usually has to be supported by other units in a potential cluster, both in order to exceed market barriers and to realise a minimum reliability of power provision.

ii. A spatially constrained neighbourhood of agents is formed referring to the physical grid topology, thus intending to incorporate the expected strain of local power grid assets due to the realisation of the cluster's schedule into the clustering process.

iii. A cluster of agents supporting the common product organises by means of agent communication in the neighbourhood of the initiator. Clustering has already been discussed in section 3, but here some other criteria for cluster formation mentioned at the beginning of this section have to be respected.

iv. During cluster formation, agents have to consent on a (fair) distribution key for the added value proceeded by the cluster after successful biding at the market and delivering the product.

b) Representation of flexibilities in possible schedules

A compact and efficiently manageable representation of the set of all possible schedules of a unit within a given time frame is a rather complex problem. Depending on the timely resolution of the schedule and the possible power settings of the units, the number of theoretically possible schedules can be in the range of 10^{100}. Additionally, distributed energy resources have to obey technical, economical or user defined constraints in their operation that restrict the set of feasible schedules. Within a cluster consisting of units owned by different individuals or companies, these constraints might be confidential and not to be communicated with the cluster. In (Bremer et al 2011) we presented a method for representation of complex structured sets of feasible schedules by means of support vector classification. This method not only hides constraints from being explicitly communicated to the virtual control unit of the cluster, but also allows integrating additional key values like cost or CO_2 emission of the schedules into an optimisation process (Bremer/Sonnenschein 2013a). An essential advantage of this method is its ability to map each potential schedule to a 'similar' feasible schedule (Bremer/Sonnenschein 2013b). This feature is required for an efficient distributed optimisation technique because it allows for the navigation in an unconstrained search domain, thus significantly reducing the complexity of possible optimisation approaches.

c) Distributed optimisation of schedules

After having succeeded in bidding a product (i.e. cluster schedule) at the energy market, a cluster has to optimise the schedules of the participating units in such a way that the benefit of the cluster – and thus the value distribution to the participation units – is maximised. RES have to be integrated into this optimisation process on the basis of a prognosis of their power production. The result of this optimisation is an operation schedule of the cluster combining the power schedules of the participating units. To this end, a distributed constraint optimisation technique for high-order constraints like COHDA (Hinrichs et al. 2013) has to be combined with the efficient representation of feasible schedules as discussed above. An additional important (but currently unsolved) question is how the reliability of product delivery can be affected positively by this optimisation. This aspect certainly requires a distributed multi-criteria optimisation to be implemented. Above all, the optimised operation schedule has to be approved by a power flow calculation (Wolter et al 2010) for grid compatibility.

d) Rescheduling of units

After having successfully bidden at the energy market, a cluster is bound to deliver the power product – otherwise it will be punished by a surcharge defined in the market rules. For several reasons, units in a cluster might be unable to deliver their contribution to the overall power schedule selected in the optimisation phase. Particularly RES possibly deviate in their power delivery from their prognosis. Therefore, a cluster must be able to reschedule power production between the participating units to meet the overall power schedule. Rescheduling again is a multi-criteria distributed constrained optimisation problem (Modi et al 2005). Besides economical and reliability related criteria, it is an important issue that the effects of the new operation schedule onto the power grid are similar to the original operation schedule in order to avoid or at least minimise the necessity for control measures of the grid operator (e.g. to react to violations of the local voltage levels). Therefore, in (Nieße/Sonnenschein 2013) we presented a method to integrate a static view of grid characteristics into the (re-)scheduling of units.

5. Conclusion

With the example of charging/discharging of EVs we have shown how intelligent units in a future smart grid can support local demand/supply matching. Clusters of small units can be scheduled for demand side management and hence reduce load peaks in a part of the grid. Self-organising, decentralised methods allow adapting clusters dynamically to changing sets of units and the predictions of their reaction to control signals. Such methods can also be used to organise dynamic virtual power plants allowing RES combined with controllable units to bid at a power market.

In the near future, more and more units in the grid have to cooperate for a safe and reliable operation of power grids. This requires a smart grid enabling local supply/demand matching as well as provision of ancillary services in the distribution grid. Agent based, distributed control and self-organisation are promising methods to cope with the requirements of adaptivity and scalability of a smart grid.

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