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Conjoint Dynamic Aggregation and Scheduling Methods for Dynamic Virtual Power Plants

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***Abstract*—The increasing pervasion of information and communication technology (ICT) in energy systems allows for the development of new control concepts on all voltage levels. In the distribution grid, this development is accompanied by a still increasing penetration with distributed energy resources like photovoltaic (PV) plants, wind turbines or small scale combined heat and power (CHP) plants. Combined with shiftable loads and electrical storage, these energy units set up a new flexibility potential in the distribution grid that can be tapped with ICT-based control following the long-term goal of substituting conventional power generation. In this contribution, we propose an architectural model and algorithms for the self-organization of these distributed energy units within dynamic virtual power plants (DVPP) along with first results from a feasibility study of the integrated process chain from market-driven DVPP formation to product delivery.**

***Index Terms*—Smart Grid, Virtual Power Plant, Agent-Based Control, Self-Organization.**

I. Introduction

DISTRIBUTED energy resources like photovoltaic (PV) plants, wind turbines or small scale combined heat and power (CHP) plants entered the energy market in many European countries, especially Germany, with the financial security of guaranteed electrical feed-in tariffs. With their share in the market still rising, a concept is needed to integrate them into the very same regarding both real power and ancillary services to reduce subsidy dependence and follow the goals as defined by the European Commission.

Virtual power plants are a well-known concept for the aggregation of distributed energy resources (DER) to deliver both energy products and ancillary services [1]. Besides the control of generation by distributed energy resources like e. g. photovoltaic plants, shiftable loads like heat pumps, water boilers or air conditioners can be controlled to adapt the load profile regarding different optimization targets. Electrical storage may additionally be a new player in this scene, delivering even more flexibility for the optimized use of distributed generation. To address these three aspects, generation, load and storage, we will refer to distributed energy units (DEU) for the rest of this paper.

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In this contribution, we present an architectural model and algorithms for conjoint distributed aggregation algorithms using flexibility modelling and distributed scheduling heuristics. We present the evaluation environment that will be used for the evaluation of these conjoint processes within dynamic virtual power plants (DVPP) for the use case of active power delivery on current energy markets like the European Power Exchange (EPEX SPOT), along with first results from a feasibility study implementing these processes. In developing the integrated process shown here, we followed the Smart Grid Algorithm Engineering (SGAE) approach described in [2].

To tap the full flexibility potential of all energy units in the distribution grid we set up the following domain-driven paradigms for DVPPs (cf. [3]):

- Distributed energy units have to trade their services on markets, for both active power products, and ancillary services (as far as possible; see e. g. [4] for the position of the German Federal Network Agency regarding this topic).
- To dynamically adapt to current power system operational states and handle the vast amount of DEU in the distribution grid, an approach based on self-organization principles is used. By this means, characteristics like robustness, scalability and adaptivity of the overall system should be gained.
- DVPPs should be set up on a per-product base, thus allowing for optimal aggregation of energy units regarding the products needed. The paradigm of a dynamic VPP with respect to the product obligation is completely different from current virtual power plant concepts. It has to be evaluated, if more flexibility can be extracted from the distribution grid with such a highly dynamic approach.
- The potential of DVPPs for power system control lies in their units' flexibility. Therefore a generic representation of these flexibilities is needed, building the foundation for all DVPP mechanisms concerned with DEU scheduling.
- For active power delivery on energy markets, the operation of DEUs is controlled using operation schedules for all different types of units. The resolution of the DEUs' operation schedules should reflect current schedule resolutions by indicating mean active power values

for each 15 min. time interval. This is different to the current handling of renewable energy sources – current systems work with prognoses and use schedules only for controllable generating electricity units.

- To deliver ancillary services with locality constraints (like voltage control), DVPPs have to be able to reflect the grid topology. Therefore grid topology should be an optional parameter in the aggregation process and within the operation of DVPPs.

Within this context, the objective of this contribution is to introduce a seamless process chain for day-ahead based active power provision by means of DVPPs. We present an integrated multi-agent system (MAS) realizing the aggregation algorithm, the scheduling heuristic as well as the flexibility modelling used for DVPP management. For this, we start with an overview on the state of the art regarding distributed control in energy systems in Section II and show why this control scheme is appropriate for DEU interaction on energy markets. In Section III we introduce the use case of active power delivery on day-ahead markets in detail. In Section IV the algorithms for the aggregation of agents to dynamic VPPs are explained, showing how grid topology is a guidance in this process without yielding hierachically restrained static aggregation schemes. The scheduling of DEU is depicted in Section V. In Section VI the generation of surrogate models to represent DEU flexibilities is explained. The integrated agent model with respect to the generation and usage of this surrogate model is shown in Section VII. The evaluation architecture and first results from a feasibility study are presented and discussed in Section VIII. We finish this contribution with a conclusion and an outlook on future work in Section IX.

II. Distributed Control in Energy Systems

The operational management of energy systems involves a number of complex tasks ranging from technical aspects like supervisory control and data acquisition (SCADA) to organizational measures performed by business management systems (BMS). These are coupled within an energy management system (EMS) based on information and communication technology (ICT). Traditionally, the EMS is implemented as a centralized control system. However, given the increasing share of DEUs in the distribution grid today, the evolution of the classical, rather static (from an architectural point of view) power system to a dynamic, continuously reconfiguring system of individual decision makers endangers the feasibility of such centralized control schemes. In the seminal work of Wu et al. [5], the need for decentralized control has been identified as follows: "Control centers today are in the transitional stage from the centralized architecture of yesterday to the distributed architecture of tomorrow. [...] To summarize, in a competitive environment, economic decisions are made by market participants individually and system-wide reliability is achieved through coordination among parties belonging to different companies, thus the paradigm has shifted from centralized to decentralized decision making." In line with this vision, the International Energy Agency (IEA) describes a possible transition to decentralized control in three steps [6]:

1) **Accommodation.** Distributed generation is accommodated into the current market with the right price signals. Centralized control of the networks remains in place.
2) **Decentralization.** The share of DG increases. Virtual utilities optimize the services of decentralized providers through the use of common communications systems. Monitoring and control by local utilities is still required.
3) **Dispersal.** Distributed power takes over the electricity market. Microgrids and power parks effectively meet their own supply with limited recourse to grid-based electricity. Distribution operates more like a coordinating agent between separate systems rather than controller of the system.

The concept of a *virtual utility* mentioned therein was introduced in the late nineties and describes a "[...] flexible collaboration of independent, market-driven entities that provide efficient energy service demanded by consumers [...]." [7] Virtual power plants (VPP) have been studied extensively as a derivation from this concept with a number of successful realizations [8]. Additionally, different operational targets have been defined and implemented for VPPs, like aggregating energy (commercial VPPs) or delivering system services (technical VPPs) [1]. These VPP concepts form a basis for the decentralization stage in the transition path above. However, such VPPs usually focus on the long-term aggregation of generators (and sometimes storages) only and are each still operated in a centralized manner. For an implementation of the dispersal stage in the transition path, a more flexible concept is required. In the last years, a significant body of research emerged on this topic. For instance, [9] surveys the use of agent-based control methods for power engineering applications. Exemplary applications can be found in [10], [11], [12]. Finally, a research agenda in this context was proposed recently in [13].

In contrast to the work referenced above, the concept of DVPPs explicitly takes the current market situation into account for the process of forming aggregations of DEUs: DVPPs form with respect to concrete products at an energy market, and will dissolve after delivering a product. Additionally, fully distributed control algorithms are being used, as will be shown in the following sections, building the foundation for the dispersal stage in the mentioned transition path. A preliminary description of the concept including a detailed differentiation from related approaches was given in [3].

III. Dynamic Virtual Power Plants

To introduce the concept of dynamic virtual power plants and show which tasks have to be performed by the software agents, we refer to the use case of active power products traded on the day-ahead power market, where product trading is based on an auction mechanism as described in [3] (see Fig. 1). From the market perspective, three different phases have to be distinguished. In the first phase, bids can be placed in the so-called order book for predefined product types. Once the

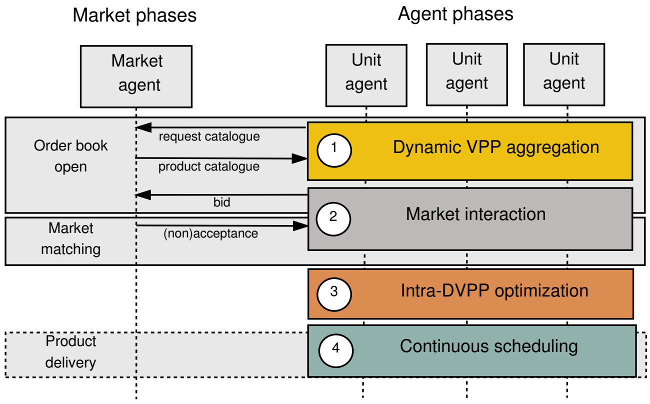

Fig. 1. Simplified use case of a dynamic VPP delivering energy products on a day-ahead market

order book is closed (e. g. at 12 a.m. for active power products traded day-ahead in Germany at EPEX SPOT) a matching mechanism clears supply and demand bids to set up the market price. In the last phase, these products have to be delivered, but no distinct market actions are entangled with this phase: the surveillance of product delivery and associated actions for balancing are subject to balancing group management.

To implement this process with regard to DVPPs, unit agents are set up to represent distinct DEUs within a multi-agent system. Four sequential phases within these unit agents are needed for active power delivery on day-ahead markets, as can be seen on the right hand side of Fig. 1:

1) **Dynamic VPP aggregation:** First, energy units have to be appropriately aggregated to DVPPs with the goal to deliver active power products. Grid topology has to be an optional parameter in this phase.
2) **Market interaction:** In the second phase, DVPPs place their active power products on the market by means of a *representative* agent for each respective DVPP and are informed about acceptance after market matching. Thus, after market matching the units' obligations regarding their power contributions are known.
3) **Intra-DVPP optimization:** Within a third phase, an intra-DVPP optimization is performed, taking into account these obligations and updated prognoses regarding the units' operational states.
4) **Continuous scheduling:** The last phase is concerned with continuous energy scheduling to ensure product fulfillment. In case of an incident endangering product delivery a rescheduling of the units has to be performed.

In Fig. 2 the same process is shown from a more detailed perspective regarding the software agents. An exemplary energy unit is shown on the left hand side that is controlled by a unit agent. To the right of this unit agent, one additional unit agent is shown with less details as example for all other unit agents. Last, a market interaction agent is shown. Details on the different agent roles during DVPP setup are given in Section IV.

In the first phase of dynamic VPP aggregation, the agent *unit_agent_1* identifies relevant market products via an interaction with the market agent. With this information, it starts the VPP aggregation process. The result of this process is a (product-specific) DVPP consisting of a set of unit agents, with a designated *representative* and a DVPP schedule mapping the DEUs to operation schedules in such a way that the product can be fulfilled.

In the next phase (market interaction), the *representative* bids at the market. After market matching, it is informed about the product to be delivered. The *representative* communicates the needed contributions to all other unit agents within the DVPP. A unit agent might have proposed active power delivery of his unit in several DVPPs (e. g. for adjacent hourly time intervals, i. e. different power products). As all obligations are known to all unit agents within the DVPP after market matching, an optimization can use remaining flexibilities. For all DEU within the DVPP, updated forecasts and measurements can be used to optimize product delivery in this step, before configuring the units with these optimized schedules.

All unit agents have to follow the same task in the last phase, from unit schedule configuration until the product delivery is finished: They have to ensure the delivery of the DVPP active power product. Therefore, the unit agents continuously (e. g. on a minute base) check the unit's operational state and check it for schedule compliance. If a unit is not following the desired schedule and if the overall DVPP active power contribution will not fulfill the defined product as a consequence, a rescheduling is performed within the DVPP agents.

In the following sections we will focus on the algorithmic details of the aforementioned steps.

IV. Dynamic Aggregation

The problem of dividing the unit agents into several DVPPs can be generally described as coalition structure generation (CSG) problem. Goal of CSG is to find an optimal partition of a given set of agents A, referred to as coalition structure (CS). The elements of a coalition structure are coalitions (C) and can be evaluated using a value function $v(C)$, where the value of a coalition structure, $V(CS)$, is calculated as the sum of values of all comprised coalitions. Goal of a CSG algorithm is to maximize $V(CS)$. There are different algorithmic solutions for CSG problems, including dynamic programming, anytime optimal solution strategies and heuristic approaches [14]. The dynamic aggregation process described in the following provides a heuristic solution to the CSG problem. For a detailed description of the considered setting see also [15].

The dynamic aggregation of energy units takes place within a defined market area which is represented by a power grid comprising a set of connected DEUs. Each DEU is supervised by a unit agent as described in the previous section. General goal of the aggregation process is an optimized provision of active power on a global level. To this end, agents are generally able to cooperate in order to form coalitions and aggregate the capabilities of their supervised DEU. The purpose of each coalition is the provision of a day-ahead active power

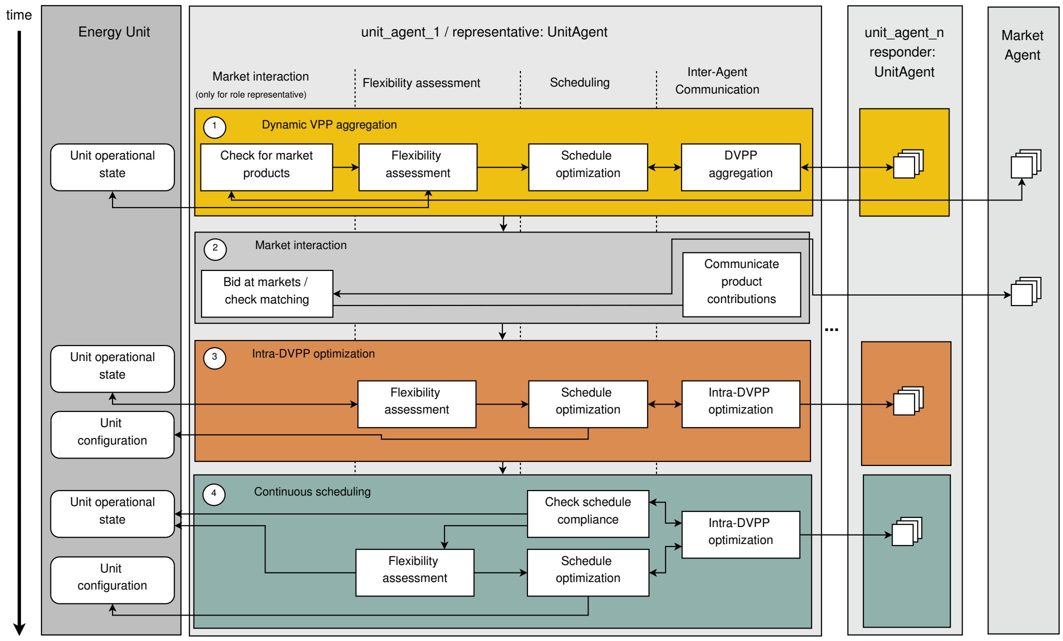

Fig. 2. Agent tasks for DVPP setup, market interaction and product delivery

product which is intended to be supplied within a corresponding product horizon reflecting the time of fulfillment. Thus, the process of DEU aggregation directly corresponds to the one of forming coalitions of supervising unit agents. Each agent contributes to an aspired power product by providing an amount of electrical energy according to the operational potentials of its energy unit. As optimization criteria, agents take the aspired target product as well as the respective costs of provision into account.

In accordance with the requirements and paradigms described in Section I, our proposed mechanism for unit aggregation is based on the principle of self-organization where agents form coalitions without external control of a superior instance. Moreover, aggregation takes place in a fully distributed and temporally flexible fashion, meaning that the organizational binding resulting from common product procurement is restricted to the provision of a provided product only and coalitions dissolve after their fulfillment. The mechanism is an iterative process, each cycle consisting of four activities which are carried out by each agent with the goal of forming coalitions with other unit agents and thus aggregating respective operational capabilities of their supervised energy units:

1) **Product portfolio generation:** In the course of the first activity an agent creates an individual product portfolio comprising a set of target products which it is generally willing to trade on the market. These target products satisfy all operational constraints of its supervised unit (like minimum operation time) as well as the product constraints obliged by the market (like maximum price/kWh). Generally, in this step several markets of same or different kind (like active power or reserve control markets) could be integrated into the decision making process in order to optimize benefit. However, our current work is restricted to a single day-ahead active power market only.
2) **Neighbourhood formation:** Given the set of target products as well as a distance function quantifying physical distance between DEUs in the grid, agents start forming neighborhoods which comprise potential cooperation partners for forming coalitions given the constraint that their supervised units are located within a specified range of physical proximity. This second activity allows unit agents to initially reduce communication and computation costs in the course of the actual aggregation process. Moreover, by taking the grid topology into account, coalitions are generally able to provide grid-sensitive power products within a specified area of the grid and thus to procure respective system services like redispatch capacities for congestion management.
3) **Coalition formation:** As third activity, agents start unit aggregation by forming coalitions within their afore defined neighborhoods in order to collectively fulfill common target products. In case an agent is not able to find a suitable coalition within its current neighborhood, it iteratively goes back to the second step and extends the scope of its neighborhood in order to include more potential cooperation partners.
4) **Payoff division:** Finally, after unit aggregation has finished and a coalition's product was accepted on the market (e. g. after clearance on an exchange), agents enter the last task and divide the payoff received from common product fulfillment among each other based on agreed criteria like contributed energy amount or reliability of procurement. To allow a fair division, the

payoff is distributed based on game-theoretic concepts [16].

V. Scheduling of units in planning and operation

The scheduling of energy units within DVPPs can be regarded as 0-1 multiple-choice combinatorial optimization problem. In this type of problems, multiple sets or classes of elements (i. e. feasible operation schedules in our use case) are given, from which each exactly one element has to be chosen to form a solution. The goal is to find a solution that minimizes (or maximizes) a given objective function (e. g. power product fulfillment).

Many problems solved by multi-agent systems are modeled as distributed constraint optimization problems (DCOP). According to [17], in a DCOP, a number of independent agents each control the state of (a subset of) the variables in the system, with the joint goal of maximizing the global reward for satisfying constraints. If global constraints affect a larger subset of agents and the problem should be solved in a distributed manner though, classical DCOP methods are not feasible. Hence, in our concept, we use the Combinatorial Optimization Heuristic for Distributed Agents (COHDA) for all scheduling aspects throughout the process (see [18] for details including an overview on and discussion of alternative solutions for this problem).

A. Intra-DVPP optimization

In the considered use case of day-ahead power provision, there will be a significant time span between market matching and product delivery (e. g. 12 hours for the EPEX SPOT in Germany). This available time span will be used for an internal optimization within a DVPP prior to product delivery. Here, updated prognoses and measurements for each DEU can be utilized in order to tap the full potential of the unit's flexibility, which allows for optimizing the unit's schedule with respect to accuracy and reliability. For example, the operational state of a combined heat and power plant in combination with new measurements of e. g. the water temperature for an attached hot water storage are used to recalculate the unit's flexibility (the modelling of a units' flexibility is described in Section VI). With this new information, a rescheduling for the units within a DVPP is performed: The obligation of a DVPP is given in the form of a power product that comprises an active power profile for a defined planning horizon (e. g. the next 24 hours) as a series of constant amounts of active power (e. g. hourly intervals, as is common for the EPEX SPOT). The optimization goal in this phase is to find a schedule for each DEU of the DVPP such that the sum of all schedules matches the power product as close as possible. However, each unit agent must be permitted to decide itself which schedule it contributes. This way, economically or ecologically rooted soft constraints can be taken into account as secondary optimization goals while preserving privacy and autonomy of the participating units. Thus we employ the self-organizing heuristic COHDA as described in [19], [18] for this task as follows.

The key concept of COHDA is an asynchronous iterative approximate best-response behavior, where each unit agent reacts to updated information from other agents by adapting its own selected schedule with respect to the power product. In order to reduce the communication overhead of this distributed optimization problem, the unit agents are placed in an artificial communication topology (e. g. a *small world* topology), such that each unit agent is connected to a non-empty subset of other unit agents. To compensate for the resulting non-global view on the system, each $unit\ agent_i$ collects two distinct sets of information: on the one hand the believed current configuration γ_i of the system (that is, the believed current schedules of all unit agents), and on the other hand the best known combination γ_i^* of schedules with respect to the power product it has encountered so far. Recall that an agent initially only knows its own flexibilities, and the difficulty of the problem is given by the distributed nature of the system in contrast to the task of finding a common allocation of schedules. Thus, the agents coordinate via message exchange. Beginning with the *representative* of the DVPP, each $unit\ agent_i$ executes the following three steps, cf. [18]:

1) (**`update`**) When a $unit\ agent_i$ receives information from one of its neighbors (say, $unit\ agent_j$), it imports these information (γ_j and γ_j^*) into its own knowledge base by updating γ_i and, if better, replacing γ_i^* with γ_j^*.
2) (**`choose`**) If γ_i or γ_i^* has been modified in the previous step, the agent adapts its own schedule according to the newly received information, while taking its own local objectives into account. If it is not able to improve the believed current system configuration γ_i, the configuration γ_i^* will be taken instead. The latter causes $unit\ agent_i$ to revert its current schedule to the one stored in γ_i^* (note that γ_i^* contains a schedule for each agent in the system and $unit\ agent_i$ takes its own of course).
3) (**`publish`**) If γ_i or γ_i^* has been modified in one of the previous steps, the agent finally publishes its knowledge base (γ_i, including its own selected schedule, and γ_i^*) to its neighbors. Local objectives are not published to other agents, thus maintaining privacy.

The algorithm terminates when for all agents γ and γ^* are identical. At this point, γ^* is the final solution of the heuristic and contains exactly one schedule for each unit in the DVPP. With this information, the unit agent configures its respective DEU by setting the schedule.

B. Continuous scheduling

Once the internal optimization has finished, operation schedules for each DEU are known to the unit agents. These schedules can now be transferred to the respective DEU of each unit agent as set values.[1] However, incidents of several types may have rendered the chosen operation schedules

[1] Appropriate communication technology choice and information modeling is not subject of this paper. For example, data can be modelled using state-of-the-art international standards and protocols like OPC UA and CIM [20].

infeasible, like DEU breakdown, updated forecasts or the operation of the DEU for unforeseen services like system services. Therefore a rescheduling is needed in those cases, where the summed deviations of the DVPP's energy units enhinder product fulfillment. To detect this behavior, the unit agents continuously monitor their DEU. If product fulfillment cannot be guaranteed anymore, rescheduling is triggered. The scheduling heuristic COHDA described in Section V-A is used for this application as well, but additional constraints and optimization criteria have to be considered beside the target product to be delivered:

- **Local DEU contraints:** As the DEUs are already in execution of a given operation schedule, reconfiguration of the unit should take care of the DEU's current operational state. In the algorithmic framework presented here, surrogate models are used to cover this task: A simulation model is initialised with the current operational state of the DEU to deliver feasible sample schedules. Thus local constraints are covered by each operation schedule retrieved from this surrogate model.
- **Robustness:** The schedules generated during internal optimization may still hold severe uncertainty regarding their feasibility. With the product delivery period approaching or even started, robustness of a DEU for a chosen schedule becomes more important, as a repeated rescheduling by the agents and resulting reconfiguration of the DEU may result in suboptimal overall system performance. Therefore the weighting of robustness may increases over time depending on the specific facets of robustness important in the context of DEU scheduling, i. e. soft constraints within the operation of DEU and power grid feasibility margins.
- **Cost:** As long as there is still enough time left until product delivery, the cost of the schedules is the most important optimization criterion. A bad robustness value can be compensated by rescheduling. When product delivery has started though or not enough time is left for rescheduling, robustness can outbalance the costs if product delivery is threatened and thus other costs (e. g. for balancing energy) would severely cut the DVPP profits. Therefore the weighting of costs decreases over time.

The optimization function for continuous rescheduling therefore has to be formulated as time-dependent optimization function, where these factors are convexly combined and given hard constraints like product fulfillment and other criteria (e. g. power grid related criteria) are taken as side conditions. The details on this are subject to current work.

VI. Representing flexibilities with surrogate models

Real world scheduling problems often face nonlinear constraints. This set of constraints defines the shape of a region within the search space (a hypercube defined by operation parameter limits) that contains all feasible solutions. This feasible region might be arbitrary shaped or discontinuous and defines the region where to pick feasible solutions from. Several techniques for handling constraints during optimization have been developed. Nevertheless, almost all are concerned with special cases of non-linear programs or require a priori knowledge of the problem structure in order to be properly adapted [21]. A good overview can be found in [22] or [23].

At the same time, support vector machines and related approaches have been shown to have excellent performance when trained as classifiers for multiple, especially real world problems. Tax and Duin developed the support vector domain description as a one-class support vector classifier that is capable of modeling the region that is defined by some given training data [24]. We adapted this concept for integrating constraints into optimization in a way that allows for efficiently navigating the feasible region. The basic idea is to construct a mapping from the whole, unconstrained domain of the problem (the hypercube) to the feasible region to be able to automatically repair infeasible solutions during optimization. In this way, the scheduling problem is transferred into an unconstrained one by mapping any arbitrary solution onto a nearby feasible one.

Information about the flexibility of a DEU, i. e. the capability to alter energy production or consumption, is indispensable for coordinating processes within a DVPP. Planning for a product specific adaption of operations demands for a detailed model of a unit's scope of action. Taking into account all feasible alterations of operation, flexibility can be represented as the set of realizable (operable without violating any constraint) schedules. Unfortunately, a full assessment of this set is in general intractable. Depending on the time resolution of the schedule and possible operational settings of a unit, the number of theoretically realizable schedules can be in the order of some 10^{100}. Each unit has to obey individual technical, economic or user defined constraints in their operation that restrict the set of feasible schedules resulting in an individually shaped feasible region. Thus, the search space that defines feasible solutions of each unit forms an individually shaped feasible region. A mathematical model of the flexibility has to be derived repeatedly on demand as it depends on the current setting (e. g. operation state) and on recent forecasts (e. g. on thermal demand). Furthermore, because a DVPP continuously re-organizes in our approach, a mathematical optimization model for a DVPP cannot be determined statically in advance. Thus, with a newly formed DVPP the model for scheduling has to be re-built according to the participating units and their individual current flexibility. Hence, we use surrogate models for a unit's flexibility as proposed in [25]. The core of the model for the set of feasible schedules is a one-class support vector classifier trained with a set of operable example schedules. This flexibility model works as follows: Given a set of sample schedules, a description of the inherent structure of the feasible region of a unit is derived. After mapping the data to a high dimensional feature space by means of an appropriate kernel, the smallest enclosing ball in this feature space is determined. When mapping back this ball to data space, the pre-image of the ball forms a set of contours (not necessarily connected) enclosing the given data sample (in our case: the feasible schedules of the respective DEU). The result of this procedure is a decision function that in general allows deciding on an arbitrary data point whether it belongs to the same region that contains the other data or not. In our use case, it allows testing a schedule wether it can be operated by the DEU or not.

But, for a controlled construction of solutions we have to go one step further, as we want to have a means for a goal-oriented search that allows us to systemetically find feasible schedules. In this way, we need a means that guides any algorithm where in the search space to look for feasible schedules. The advantage of our model is that it allows to generate a decoder that transforms the problem of distributed active power planning into an unconstrained one [26]. In general, a decoder is a constraint handling technique that imposes a relationship between feasibility and decoder solutions in order to give an algorithm hints on how to construct a feasible solution [23]. The flexibility of a unit is represented as pre-image of a high-dimensional ball. This representation has some advantageous properties. Although the pre-image might be some arbitrary shaped non-continuous blob in $\mathbb{R}^d$, the high-dimensional representation is still a ball and thus geometrically easier to handle. The relation is as follows: If a schedule can be operated without violating any constraint, it lies inside the feasible region. Thus, it is inside the pre-image (that represents the feasible region) of the ball and thus its image in the high-dimensional representation lies inside the ball. An infeasible schedule lies outside the feasible region and thus its image lies outside the ball. Additionally, we know some relations: the center of the ball, the distance of the image from the center and the radius of the ball. Hence, we can move the image of an infeasible schedule along the difference vector towards the center until it touches the ball. Finally, we calculate the pre-image of the moved image and get a schedule at the boundary of the feasible region: a repaired schedule that is now feasible. We do not need an explicit mathematical description of the feasible region or of the constraints to do this. Working with this decoder concept comprises two successive stages:

1) **A model/decoder training phase:** During the training phase (flexibility assessment) the decoder is build out of an set of example schedules derived from a simulation model of the unit.
2) **A successive planning phase:** Once the model is built, it can be (re-)used for assessing the feasibility of arbitrary schedules and for systematically generating feasible schedules with the decoder.

The latter is the main use case for the flexibility model: Whenever a prospective schedule is generated as a candidate solution to a specific unit, the decoder is used to convert this schedule into a similar schedule that is guaranteed to be operable by this DEU. The feasible version is used for scheduling. At the same time, performance indicators characterizing individual schedules with respect to different optimization goals are automatically preserved with this method [27]. Thus, after mapping a schedule (even with wrong or no associated performance indicators) to a feasible one, evaluation with respect to multiple criteria is possible. For distributed problem solving, the decoder can serve as a substitute for an often (particularly with regard to a fully automated generation in dynamic environments) hardly derivable mathematical model of a unit. The flexibility model automatically derives a means for generating feasible solutions from an unknown (to the agent) technical model. Hence, in our use case the flexibility model allows the agent for always working with operable schedules and thus with feasible solutions during coalition formation and scheduling without a need for a unit specific agent implementation.

VII. Agent model

In order to manage the repeatedly executed tasks of the four phases (DVPP aggregation, market interaction, intra-DVPP optimization, and continuous scheduling) the automaton depicted in Fig. 3 is guiding each agent through the process. Once started, the agent first executes the flexibility assessment task by querying the current state of the controlled unit and simulating possible flexibilities with its parameterization. The flexibility model and the decoder are built and provided for reuse in successive tasks. If the agent is not yet part of a DVPP, the agent takes part in the aggregation process that as a result assigns the agent to a newly formed DVPP. After forming the DVPP each agent participates in a continuous optimization process that aims at assigning a schedule to each agent's unit such that correct delivery of the product is ensured as reliable and at the same time as efficiently as possible. To do this the described optimization process is executed. The first execution is started at latest directly before product delivery. In case of an event that invalidates the current flexibility model due to changed assumptions or technical problems, the flexibility assessment has to be started again. With this new flexibility model, the optimization process may then be executed for rescheduling as a reaction to the event. The rescheduling may be triggered without a new flexibility assessment in case it is triggered due to the invalidation of another agent's flexibility model. After product delivery the DVPP's existence comes to an end and the cycle starts again.

VIII. Feasibility study

A. Simulation Environment

The purpose of distributed control concepts as described in this work is to realize an agent-based control of distributed energy units according to a current market situation, the current energy unit's state and the power grid's operational state. As a consequence, purpose of the evaluation system is to evaluate the effect of these distributed control concepts on the energy units and (for some applications) the power grid. Therefore a Smart Grid simulation has to be performed, following requirements regarding the reuse of existing models, a convenient and easy to reuse scenario specification, a well-defined API to real-world components and a synchronization concept and implementation between the multi-agent system

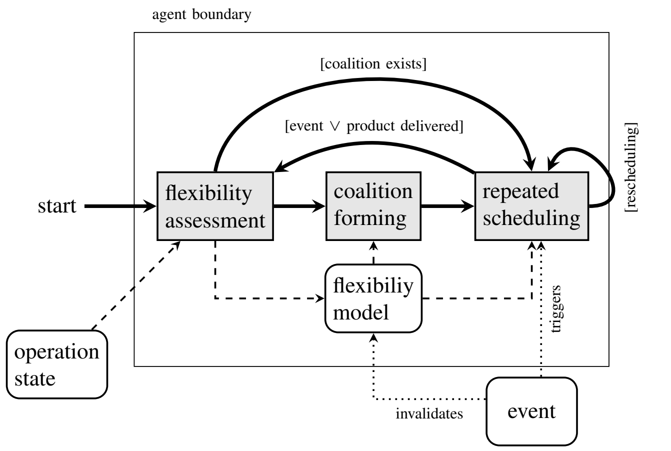

Fig. 3. Flow chart of the agent model with control flow (solid), data flow (dashed) and trigger (dotted)

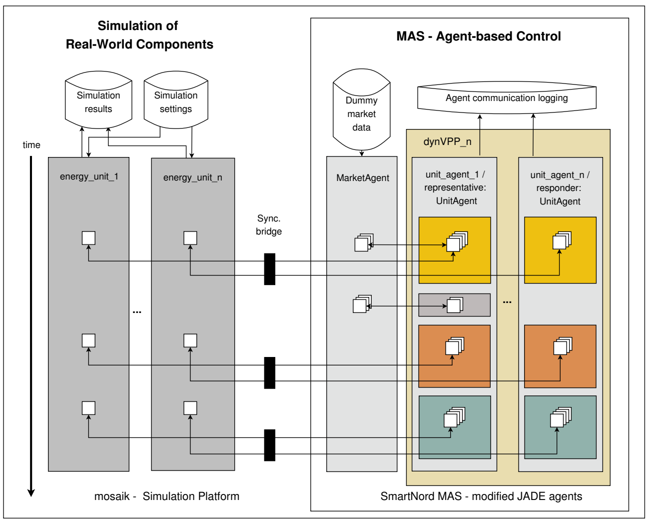

Fig. 4. Evaluation system with unit simulation using mosaik, multi-agent system for control of the VPP and synchronisation agent.

and the Smart Grid simulation. We use mosaik [28] as Smart Grid simulation framework that was built to meet these requirements. The chosen Smart Grid simulation framework has to be coupled with the distributed control technology framework chosen. In our case, we chose JADE [29] with some modifications.[2]

In Fig. 4 an overview on the evaluation system is given. Smart Grid simulation and agent-based control are completely separated. On the left hand side, the Smart Grid simulation with all simulation models for DEU is shown. On the right hand side, the MAS is shown. Within this part of the MAS, the agent-based control of the simulated real-world components (that is DEU in the use case chosen here) is realized. During simulation, the unit agents have to access the simulated energy units to set schedules and retrieve current measurement values. This access is realized using a synchronization bridge (depicted in in the middle of Fig. 4) offering a JADE interface. Besides data transfer, the bridge handles the sychronisation between Smart Grid simulation and MAS. The agents cannot distinguish being run in a simulation environment or in a real-world application. Within mosaik, the bridge allows to handle the MAS as an additional simulation component. In our system, dummy market data serve as input for the market agent to define products and realize the market matching once the order book is closed. The output data of both Smart Grid simulation and multi-agent system are stored in two HDF5-databases.

[2]As JADE schedules events in real-time, parts of the agent framework JADE had to be rewritten to realize this synchronization, thus allowing to run JADE as a MAS-simulation.

B. Experimental setup and results

To give an illustrative example for the integrated process chain within a feasibility study, we setup a scenario with 38 combined heat and power plants combined with thermal storage connected to households in a low-voltage grid. As product to be realized by the DVPPs we defined a product of 25 kWh from 2 p.m. to 3 p.m. on January 2nd, 2013, i. e. 15 min. time intervals 56 to 59 on day 1. The simulation was run from January 1st, 2013 (day 0) to January 2nd, 2013 (day 1) to cover the day-ahead market use case defined in Section III. The Smart Grid simulation was run with a stepsize of one minute, taking into account the weather conditions on the chosen simulation days.

We expected the following phases when running the MAS in the coupled simulation with mosaik: (1) Day-ahead flexibility assessment for all units and DVPP formation for defined product for day 1, and (2) Intra-day pre-delivery flexibility assessment for DVPP units and rescheduling of units for day 1.

We started the process of DVPP setup at 0 a.m. on day 0. Reassessment of flexibilities and rescheduling was started at 0 a.m. at day 1. In this setup, grid topology is reflected within DVPP setup as defined by the neighbourhoods (cf. Section IV).

In Fig. 5 the sample schedules for the initial flexibility assessment are shown for one energy unit ($unit_1$). For each sample schedule, the mean power value is plotted for all 96 operation schedule intervals. The distribution of power values over time is quite uniform. In the surrogate model trained with these samples (cf. Section VI), very different operation schedules can be found for the product horizon starting at interval 56 (2 p.m.). During DVPP formation, energy units aggregate to coalitions if their potential contributions fit the product needed (cf. Section IV). In the example given here units should aggregate to deliver a 25 kWh hourly product. For reasons of clarity, we only illustrate the product setup of one DVPP from this scenario. For the example DVPP chosen, 5 unit agents jointly deliver the defined product. On the left hand side of Fig. 6 the active power contributions of all energy units within the DVPP are shown as stacked chart over time for the product horizon (2 – 3 p.m.). The energy that would be delivered by the DVPP following these schedules is depicted on the right hand side. The product target of 25 kWh is not reached due to the tolerance settings within coalition

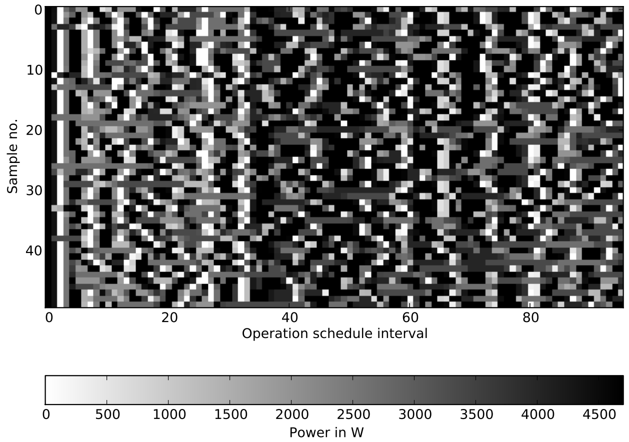

Fig. 5. Day-ahead sample schedules for $unit_1$

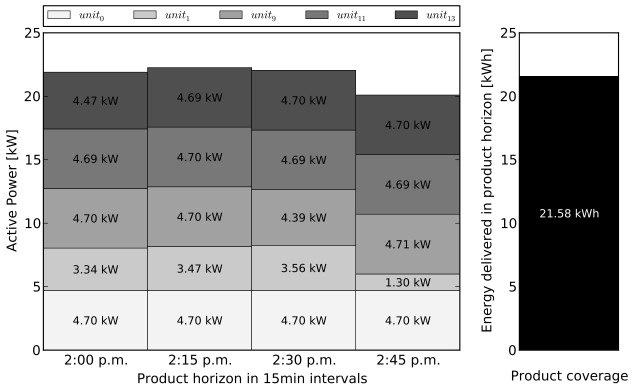

Fig. 6. Cluster schedule and product coverage after DVPP setup

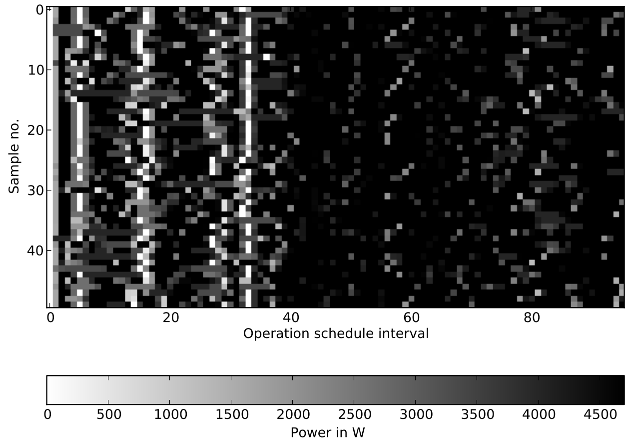

Fig. 7. Intra-day sample schedules for $unit_1$

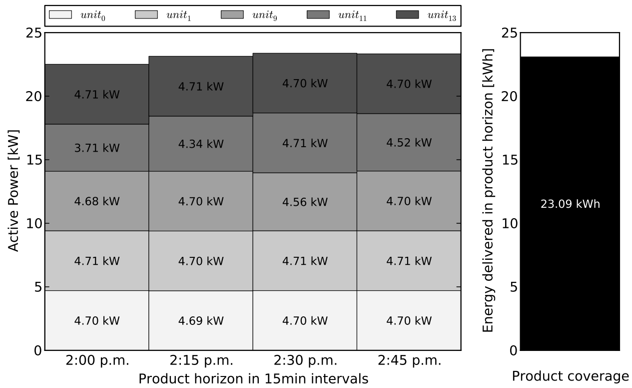

Fig. 8. Cluster schedule and product coverage after rescheduling

formation; these can be adapted individually for each product.[3]

A second flexibility assessment was triggered at 0 p.m. on day 1. Fig. 7 shows the samples taken from the simulation of the unit at that simulation time. If compared with the initial samples (Fig. 5), a much darker region can be detected at the product horizon (time intervals 56 – 59). Obviously, flexibilities in unit operation have narrowed down (e. g. due to the current capacity of the thermal storage or updated weather prognoses). The surrogate model trained with these samples will not produce schedules with power values lower than 3000 W in the chosen time horizon. We now take a closer look on the results of the planning phase using the surrogate models trained by the sample schedules from the second flexibility assessment.

In Fig. 8 the schedules after rescheduling using COHDA (cf. Section V-A) are shown. As can be seen, the product is now fulfilled better (23.09 kWh). One reason for this might be the changed surrogate model of $unit_1$: In the original plan, this unit has been scheduled with a contribution of 1.3 kW for time interval 59 (2:45 p.m.). This active power range cannot be retrieved from the surrogate model trained with the samples shown in Fig. 7, as an active power value lower 3000 W is not within the set of feasible schedules. Therefore, a new solution has been found by COHDA following both the updated flexibilities (modelled within the surrogate models of the energy units) and the target product tolerance margins.

[3]The evaluation of an optimal setting of these margins is part of a later evaluation of the overall system.

IX. Conclusion

In this paper we presented an agent-based control method for dynamic virtual power plants self-adapting their unit set and operational plan to be able to trade products on a power market. The three coordination steps of aggregation, schedule optimization, and continuous scheduling for DVPP control are integrated into the behavior of unit agents. These agents interact with each other and with the power market. Aggregation as well as scheduling of DVPPs is based on self-organization methods to achieve adaptivity to a changing set of units and new products traded on the market. So, DVPPs are self-coordinating, self-optimizing, and – within certain limits – self-healing. A cross-sectional technology for representation of the units' flexibilities is provided by a surrogate model allowing to integrate new types of units easily into the coordination mechanism of DVPPs.

A simulation-based demonstrative example of the interaction of the coordination steps of a DVPP has been given in this contribution. Based on the current state of knowledge, DVPPs are a very promising approach to exploit flexibilities of decentralized units in a future power grid to support the integration of renewable energy resources. More and particularly more complex scenarios have to be studied to evaluate the performance, stability and dynamics of this control method. This will be a significant goal in our ongoing project cluster Smart Nord.

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REFERENCES

[1] O. Abarrategui, J. Marti, and A. Gonzalez, "Constructing the Active European Power Grid," in *Proceedings of WCPEE09*, Cairo, 2009, pp. 1–4.

[2] A. Nieße, M. Tröschel, and M. Sonnenschein, "Designing Dependable and Sustainable Smart Grids – How to Apply Algorithm Engineering to Distributed Control in Power Systems," *Environmental Modelling & Software*, 2013. doi: 10.1016/j.envsoft.2013.12.003

[3] A. Nieße, S. Lehnhoff, M. Tröschel, M. Uslar, C. Wissing, H.-J. Appelrath, and M. Sonnenschein, "Market-based self-organized provision of active power and ancillary services: An agent-based approach for smart distribution grids," in *Complexity in Engineering (COMPENG)*, 2012. doi: 10.1109/CompEng.2012.6242953

[4] Bundesnetzagentur, "'Smart Grid' and 'Smart Market'," 2012, [Online; accessed 2014-01-24]. [Online]. Available: http://www.bundesnetzagentur.de/SharedDocs/Downloads/DE/Sachgebiete/Energie/Unternehmen_Institutionen/NetzzugangUndMesswesen/SmartGridEckpunktepapier/SmartGridPapier_EN.pdf

[5] F. Wu, K. Moslehi, and A. Bose, "Power system control centers: Past, present, and future," *Proceedings of the IEEE*, vol. 93, no. 11, pp. 1890–1908, 2005. doi: 10.1109/JPROC.2005.857499

[6] International Energy Agency, *Distributed Generation in Liberalised Electricity Markets*. OECD Publishing, 2002. ISBN 978-9-2641-7597-6

[7] S. Awerbuch and A. M. Preston, Eds., *The Virtual Utility: Accounting, Technology & Competitive Aspects of the Emerging Industry*, ser. Topics in Regulatory Economics and Policy. Kluwer Academic Publishers, 1997, vol. 26. ISBN 0-7923-9902-1

[8] D. Coll-Mayor, R. Picos, and E. Garciá-Moreno, "State of the art of the virtual utility: the smart distributed generation network," *International Journal of Energy Research*, vol. 28, no. 1, pp. 65–80, 2004. doi: 10.1002/er.951

[9] S. McArthur, E. Davidson, V. Catterson, A. Dimeas, N. Hatziargyriou, F. Ponci, and T. Funabashi, "Multi-agent systems for power engineering applications – Part I: Concepts, approaches, and technical challenges," *IEEE Transactions on Power Systems*, vol. 22, no. 4, pp. 1743–1752, 2007. doi: 10.1109/TPWRS.2007.908471

[10] R. R. Negenborn, Z. Lukszo, and H. Hellendoorn, Eds., *Intelligent Infrastructures*, ser. Intelligent Systems, Control and Automation: Science and Engineering. Springer, 2010, vol. 42. ISBN 978-90-481-3597-4

[11] S. D. Ramchurn, P. Vytelingum, A. Rogers, and N. R. Jennings, "Agent-based homeostatic control for green energy in the smart grid," *ACM Trans. Intell. Syst. Technol.*, vol. 2, no. 4, pp. 35:1–35:28, Jul. 2011. doi: 10.1145/1989734.1989739

[12] G. Anders, F. Siefert, J.-P. Steghöfer, H. Seebach, F. Nafz, and W. Reif, "Structuring and Controlling Distributed Power Sources by Autonomous Virtual Power Plants," in *IEEE Power and Energy Student Summit (PESS 2010)*. IEEE Power & Energy Society, 2010.

[13] S. D. Ramchurn, P. Vytelingum, A. Rogers, and N. R. Jennings, "Putting the 'smarts' into the smart grid: A grand challenge for artificial intelligence," *Commun. ACM*, vol. 55, no. 4, pp. 86–97, Apr. 2012. doi: 10.1145/2133806.2133825

[14] T. Michalak, J. Sroka, T. Rahwan, M. Wooldridge, P. McBurney, and N. R. Jennings, "A distributed algorithm for anytime coalition structure generation," in *Proceedings of the 9th International Conference on Autonomous Agents and Multiagent Systems: Volume 1 - Volume 1*, 2010. doi: 10.1.1.153.8211 pp. 1007–1014.

[15] S. Beer and H.-J. A. Appelrath, "A formal model for agent-based coalition formation in electricity markets," in *2013 4th IEEE/PES Innovative Smart Grid Technologies Europe (ISGT EUROPE)*, 2013. doi: 10.1109/ISGTEurope.2013.6695442 pp. 1–5.

[16] S. S. Fatima, M. Wooldridge, and N. R. Jennings, "A Linear Approximation Method for the Shapley Value," *Artificial Intelligence*, vol. 172, no. 14, pp. 1673 – 1699, 2008. doi: 10.1016/j.artint.2008.05.003

[17] A. C. Chapman, A. Rogers, N. R. Jennings, and D. S. Leslie, "A unifying framework for iterative approximate best-response algorithms for distributed constraint optimization problems." *Knowledge Eng. Review*, vol. 26, no. 4, pp. 411–444, 2011. doi: 10.1017/S0269888911000178

[18] C. Hinrichs, M. Sonnenschein, and S. Lehnhoff, "Evaluation of a self-organizing heuristic for interdependent distributed search spaces," in *ICAART 2013 – Proceedings of the 5th International Conference on Agents and Artificial Intelligence*, J. Filipe and A. Fred, Eds., vol. 1. Barcelona, Spain: SciTePress, 2013. doi: 10.5220/0004227000250034. ISBN 978-989-8565-38-9 pp. 25–34.

[19] C. Hinrichs, J. Bremer, and M. Sonnenschein, "Distributed Hybrid Constraint Handling in Large Scale Virtual Power Plants," in *2013 4th IEEE/PES Innovative Smart Grid Technologies Europe (ISGT EUROPE)*. IEEE Power & Energy Society, 2013. doi: 10.1109/ISGTEurope.2013.6695312

[20] S. Rohjans and M. Specht, *OPC UA: An Automation Standard for Future Smart Grids*, ser. Standardization in Smart Grids. Springer, 2013, ch. 12. ISBN 978-3-642-34916-4

[21] Z. Michalewicz and M. Schoenauer, "Evolutionary algorithms for constrained parameter optimization problems," *Evol. Comput.*, vol. 4, pp. 1–32, March 1996. doi: 10.1162/evco.1996.4.1.1

[22] C. A. Coello Coello, "Theoretical and numerical constraint-handling techniques used with evolutionary algorithms: a survey of the state of the art," *Computer Methods in Applied Mechanics and Engineering*, vol. 191, no. 11-12, pp. 1245–1287, Jan. 2002. doi: 10.1016/S0045-7825(01)00323-1

[23] O. Kramer, "A review of constraint-handling techniques for evolution strategies," *Appl. Comp. Intell. Soft Comput.*, vol. 2010, pp. 1–19, January 2010. doi: 10.1155/2010/185063

[24] D. M. J. Tax and R. P. W. Duin, "Data Domain Description using Support Vectors," in *European Symposium on Artificial Neural Networks – ESANN*, 1999, pp. 251–256.

[25] J. Bremer, B. Rapp, and M. Sonnenschein, "Encoding distributed Search Spaces for Virtual Power Plants," in *IEEE Symposium Series in Computational Intelligence 2011 (SSCI 2011)*, Paris, France, 4 2011. doi: 10.1109/CIASG.2011.5953329

[26] J. Bremer and M. Sonnenschein, "Constraint-handling for optimization with support vector surrogate models – a novel decoder approach," in *ICAART 2013 – Proceedings of the 5th International Conference on Agents and Artificial Intelligence*, J. Filipe and A. Fred, Eds., vol. 2. Barcelona, Spain: SciTePress, 2013. doi: 10.5220/0004241100910100. ISBN 978-989-8565-38-9 pp. 91–105.

[27] ——, "Automatic Reconstruction of Performance Indicators from Support Vector based Search Space Models in Distributed Real Power Planning Scenarios," in *Informatik 2013, 43. Jahrestagung der Gesellschaft für Informatik e.V. (GI)*, ser. LNI, M. Horbach, Ed., vol. 220. Koblenz: GI, 2013. ISBN 978-3-88579-614-5 pp. 1441–1454.

[28] S. Schütte, S. Scherfke, and M. Tröschel, "Mosaik: A Framework for Modular Simulation of Active Components in Smart Grids," in *1st Int. Workshop on Smart Grid Modeling & Simulation*. Brussels: IEEE, 2011. doi: 10.1109/SGMS.2011.6089027

[29] Telecom Italia S.p.A., "JADE (Java Agent Development Framework)," 2014, [accessed 2014-06-15]. [Online]. Available: http://jade.tilab.com/