Modeling Uncertainty in Support Vector Surrogates of Distributed Energy Resources
Enabling Robust Smart Grid Scheduling

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Abstract: Robust proactive planning of day-ahead real power provision must incorporate uncertainty in feasibility when trading off different schedules against each other during the predictive planning phase. Imponderabilities like weather, user interaction, projected heat demand, and many more have a major impact on feasibility – in the sense of being technically operable by a specific energy unit. Deviations from the predicted initial operational state of an energy unit may easily foil a planned schedule commitment and provoke the need for ancillary services. In order to minimize control power and cost arising from deviations from agreed energy product delivery, it is advantageous to a priori know about individual uncertainty. We extend an existing surrogate model that has been successfully used in energy management for checking feasibility during constraint-based optimization. The surrogate is extended to incorporate confidence scores based on expected feasibility under changed operational conditions. We demonstrate the superiority of the new surrogate model by results from several simulation studies.

1 INTRODUCTION

The current upheaval regarding control in the changing electricity grid leads to growing complexity and a need for new control schemes (Nieße et al., 2012). A steadily growing number of renewable energy resources like photovoltaics (PV), wind energy conversion (WEC) or co-generation of heat and power (CHP) has to be integrated into the electricity grid. This fact leads to a growing share of hardly predictable feed-in. The behavior of such units often depends on uncertain prediction of projected weather conditions, user interaction (e. g. hot water usage), or similar. An algorithm for robust control would coordinate distributed energy resources with a proactive planning that already takes into account such uncertainty issues for scheduling in order to minimize the need for ancillary services in case of deviation from planned electricity delivery. Without loss of generality, we will focus on algorithms for virtual power plants (VPP) as an established control concept for renewables' integration (Nikonowicz and Milewski, 2012) for the rest of the paper. All concepts are nevertheless applicable for different organizational structures, too.

Many balancing algorithms for a bunch of different control schemes have already been proposed as a solution to the problem of assigning a suitable, feasible schedule to each energy unit such that the sum of all schedules resembles a desired load profile while concurrently other objectives like minimal cost are met, too. Among such solutions are centralized algorithms as well as decentralized approaches for VPP as organizational entity. A VPP can be seen as a cluster of distributed energy resources (generators as well as controllable consumers) that are connected by communication means for control. From the outside, the VPP cluster behaves like a larger, single power plant. A VPP may offer services for real power provision as well as for ancillary services (Nieße et al., 2012; Lukovic et al., 2010; Braubach et al., 2009).

Traditionally, energy management is implemented as centralized control. However, given the increasing share of DER as well as flexible loads 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 (e. g. as described in (Ilić, 2007; Nieße et al., 2014)), it is unlikely for such centralized control schemes to be able to cope with the rapidly growing problem size. Thus, the seminal work of (Wu et al., 2005) identified the need for de-

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centralized control. Examples for VPP are given in (Coll-Mayor et al., 2004; Nikonowicz and Milewski, 2012). An overview on existing control schemes and a research agenda can e. g. be found in (McArthur et al., 2007; Ramchurn et al., 2012).

In order to additionally address the integration of the current market situation as well as volatile grid states, (Nieße et al., 2014) introduces the concept of a dynamic virtual power plant (DVPP) for an on demand formation and situational composition of energy resources to a jointly operating VPP. In this approach VPPs gather dynamically together with respect to concrete electricity products at an energy market and will diverge right after delivery. Such dynamic organization even more relies on assumptions and predictions about individual flexibilities of each (possibly so far unknown) energy unit when going into load planning.

Anyway, a general problem for all algorithms is the presence of individual local constraints that restrict possible operations of all distributed energy resource (DER) within a virtual power plant. Each DER first and foremost has to serve the purpose it has been built for. But, usually this purpose may be achieved in different alternative ways. For example, it is the (intended) purpose of CHP to deliver enough heat for the varying heat demand in a household at every moment in time. Nevertheless, if heat usage can be decoupled from heat production by use of a thermal buffer store, different production profiles may be used for generating the heat. This leads, in turn, to different respective electric load profiles that may be offered as alternatives to a VPP controller. The set of all schedules that a DER may operate without violating any technical constraint (or soft constraint like comfort) is the sub-search-space with respect to this specific DER from which a scheduling algorithm may choose solution candidates. Geometrically seen, this set forms a sub-space $\mathcal{F} \subseteq \mathbb{R}^d$ in the space of all possible schedules.

In (Bremer et al., 2011) a model has been proposed to derive a description for this sub-space of feasible solutions that abstracts from any DER model and its specific constraint formulations. These surrogate models for the search spaces of different DER may be automatically combined to a dynamic optimization model by serving as a means that guides an arbitrary algorithm where to look for feasible solutions. Due to the abstract formulations all DER may be treated the same by the algorithm and thus the control mechanism can be developed independently of any knowledge on the energy units that are controlled afterwards.

Up to now, this approach takes into account merely a hard margin that isolates feasible and infeasible schedules. A schedule is either feasible or not. But, in real life problems this feasibility depends on predictions about the initial operational state of the unit from which the schedule is operated. If this initial state deviates from the predicted, the schedule might or might not still be operable. The uncertainty in predicting the initial state of the unit is reflected by an uncertainty about the feasibility of any schedule. This fact results in a need for a fuzzy definition of the feasible region that contains all feasible schedules of a unit.

In this contribution, we extend the model given in (Bremer et al., 2011) to unsupervised fuzzy decision boundaries after (Liu et al., 2013) and demonstrate the superior quality when deciding on feasibility of schedules under uncertain conditions. We start with a discussion on related work and briefly recap the used model technique before we define the extension and propose a measure for the confidence of arbitrary schedules. We conclude with several simulation results that support the extended approach.

2 RELATED WORK

2.1 Uncertainty in the Smart Grid

Several works scrutinize the problem of uncertainty within the smart grid in general; mainly by using predefined stochastic models (Alharbi and Raahemifar, 2015). Uncertainty in long term development examinations like (Zio and Aven, 2011) are not in the scope of this work. Lots of work has been done in the field of wind (or photovoltaics) forecasting, e. g. (Zhang et al., 2013; Sri et al., 2007), or on integration into stochastic unit commitment approaches (Wang et al., 2011), respectively. But, so far surprisingly low effort has been spent on integration into energy resource modeling for the case of operability. In (Wildt, 2014) uncertainty about demand response is integrated directly into a multi agent decision making process, but in an unit specific and not in an abstract way. Integrating models of correlation in unit behaviour may be handled by using factory approaches for the scenario as has been demonstrated for the energy sector e. g. in (Bremer et al., 2008). An example for modeling reliability and assessment differentiated for different unit types is given in (Blank and Lehnhoff, 2014).

On the other hand, a need for an abstract unit-independent surrogate model of individual feasible regions in distributed generation scenarios can for example be derived from (Nieße et al., 2012; Hinrichs et al., 2013a).

2.2 Surrogate Models for DER

Abstract surrogate models in the energy management sector are usually built on a set of feasible schedules that serve as a training set for deriving the surrogate model. The procedure starts with initializing a unit behavior model with a parametrization from the physical unit or – in case of simulation – from its simulation model. These parameters may be directly read from the unit reflecting its current operation state or may be further projected onto a future state using the current operation schedule and predictions on future operation conditions.

Whereas in the first case exact parameters are derived, the latter case usually suffers from uncertainty from different forecast sources. The initialization defines the initial state of the unit at the starting point from whence alternative schedules are to be determined by sampling the behavior model which simulates the future flexibilities of the energy unit. If the initial operational state of the unit at the starting point of the time frame over which the energy load is balanced or optimized is fixed, a surrogate model can be derived that abstracts from the specific unit at hand and allows for an ad hoc integration at runtime into the scheduling algorithm.

Such models based on support vector approaches have been presented e. g. in (Bremer et al., 2011). We will briefly recap this technique before extending the ideas to uncertainty integration. The model is based on support vector data description (SVDD) as introduced by (Tax and Duin, 2004). The goal of building such a model is to learn the feasible region of the schedules of a DER by harnessing SVDD to learn the enclosing boundary around the whole set of operable schedules.

We will briefly introduce SVDD approach as for instance described in (Ben-Hur et al., 2001; Bremer et al., 2011). This task is achieved by determining a mapping function $\Phi : \mathcal{X} \subset \mathbb{R}^d \to \mathcal{H}$, with $x \mapsto \Phi(x)$ such that all data points from a given region $\mathcal{X}$ is mapped to a minimal hypersphere in some high- or indefinite-dimensional space $\mathcal{H}$ (actually, the images go onto a manifold whose dimension is at maximum the cardinality of the training set). The minimal sphere with radius R and center a in $\mathcal{H}$ that encloses $\{\Phi(x_i)\}_N$ can be derived from minimizing $\|\Phi(x_i) - a\|^2 \leq R^2 + \xi_i$ with $\|\cdot\|$ denoting the Euclidean norm and with slack variables $\xi_i \geq 0$ that introduce soft constraints for sphere determination. Introducing $\boldsymbol{\beta}$ and $\boldsymbol{\mu}$ as the Lagrangian multipliers, the minimization problem for finding the smallest sphere becomes

$$L(\boldsymbol{\xi},\boldsymbol{\mu},\boldsymbol{\beta}) = R^2 - \sum_i (R^2 + \xi_i - \|\Phi(x_i) - a^2)\|\beta_i - \sum_i \xi_i\mu_i + C\sum_i \xi_i. \tag{1}$$

$C\sum_i \xi_i$ is a penalty term and determines size and accuracy of the resulting sphere by determining the number of rejected outliers. Usually C reflects an a priori fixed rejection rate.

After introducing Lagrangian multipliers and further relaxing to the Wolfe dual form, the well known Mercer's theorem may be harnessed for calculating dot products in $\mathcal{H}$ by means of a Mercer kernel in data space: $\Phi(x_i) \cdot \Phi(x_j) = k(x_i, x_j)$; cf. (Schölkopf et al., 1999). In order to gain a more smooth adaption, it is known (Ben-Hur et al., 2001) to be advantageous to use a Gaussian kernel:

$$k_{\mathcal{G}}(x_i, x_j) = e^{-\frac{1}{2\sigma^2}\|x_i - x_j\|^2}. \tag{2}$$

Putting it all together, the equation that has to be maximized in order to determine the desired sphere is:

$$W(\beta) = \sum_i k(x_i, x_i)\beta_i - \sum_{i,j} \beta_i\beta_j k(x_i, x_j). \tag{3}$$

With $k = k_{\mathcal{G}}$ we get two main results: the center $a = \sum_i \beta_i \Phi(x_i)$ of the sphere in terms of an expansion into $\mathcal{H}$ and a function $R : \mathbb{R}^d \to \mathbb{R}$ that allows to determine the distance of the image of an arbitrary point from $a \in \mathcal{H}$, calculated in $\mathbb{R}^d$ by:

$$R^2(\boldsymbol{x}) = 1 - 2\sum_i \beta_i k_{\mathcal{G}}(x_i, x) + \sum_{i,j} \beta_i\beta_j k_{\mathcal{G}}(x_i, x_j). \tag{4}$$

Because all support vectors are mapped right onto the surface of the sphere, the radius $R_{\mathbb{S}}$ of the sphere $\mathbb{S}$ can be easily determined by the distance of an arbitrary support vector. Thus the feasible region can now be modeled as

$$\mathcal{F} = \{x \in \mathbb{R}^d | R(x) \leq R_{\mathbb{S}}\} \approx \mathcal{X}. \tag{5}$$

Initially, such models have for example been used for handwritten digit or face recognition, pattern denoising, or anomaly detection (Chang et al., 2013; Park et al., 2007; Rapp and Bremer, 2012). A relatively new application is that of modeling feasible regions and constraint abstraction for distributed optimization problems especially in the field of energy management, e. g. as used in (Hinrichs et al., 2013a).

Using SVDD as surrogate model within a VPP control algorithm starts with generating a training set of feasible schedules for a specific energy unit with the help of a simulation model of this unit. Thus, a schedule is a vector $\boldsymbol{x} \in \mathbb{R}^d$ consisting of d values for mean active power to be operated during the respective time inerval. In a first step, the simulation

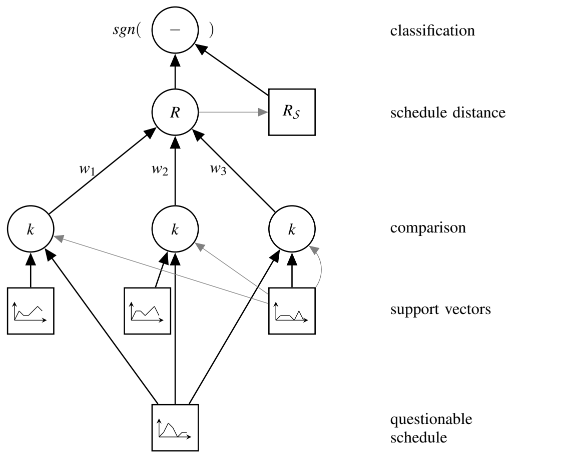

Figure 1: Scheme for using SVDD as surrogate model for checking feasibility of operation schedules in distributed energy management after (Schölkopf, 1997).

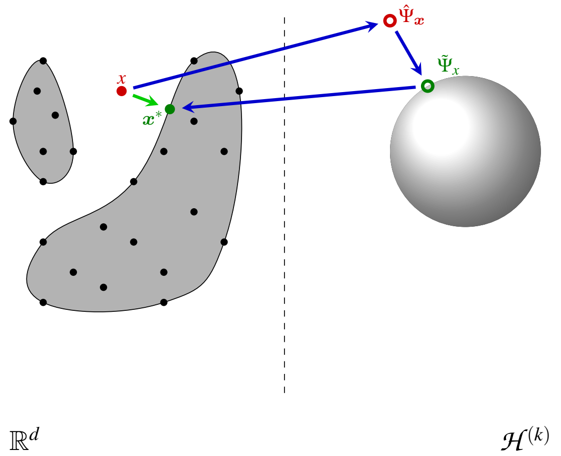

Figure 2: Basic idea of an decoder for constraint-handling based on SVDD (Bremer and Sonnenschein, 2014).

model is parametrized with the estimated initial operation state of the unit (e. g. the temperature of a thermal buffer store attached to a co-generation plant) at the future point in time that marks the start of the time frame for which a cluster schedule for the VPP is to be found. A cluster schedule as result of an (distributed) optimization process assigns a schedule to each energy unit within the VPP such that the sum of all individual schedules resembles a given target schedule (often an energy product to be sold at market) as close as possible. This simple case is an instance of the multiple choice constraint optimization problem (Hinrichs et al., 2013b); for each unit a schedule has to be chosen from the feasible region of that unit. Often, further objectives like cost are concurrently optimized. Because the units are not necessarily known at compile-time and in order to be able to implement the control strategy independently, surrogates with a well-defined interface are used for checking feasibility during optimization. In this way, a simulation model for each unit is parametrized with a predicted initial operation state and generates a training set of feasible schedules for training the SVDD classifier that in turn is used by the problem solver for checking feasibility (Bremer et al., 2011). The process of checking feasibility for the VPP case is depicted in figure 1. A so far unaddressed problem is that of integrating uncertainty issues in such models. Integrating uncertainty into support vector data description has so far led to only a few approaches. For instance, (Zheng et al., 2006) introduced a fuzzy approach for the data clustering use case. With the help of a fuzzy definition of membership that determines for each point whether it belongs to the training set or not, they control the rate of hyper volume and outlier acceptance. Another approach with fuzzy constraint treatment is given by (GhasemiGol et al., 2010). A different approach is taken in (Liu et al., 2013). An individual weighting is introduced allowing for a differentiated consideration of accepted errors. Thus, data points with a higher confidence have a larger impact on the decision boundary. Equation (6) shows the respective extension to (1) in the last term.

$$
\begin{aligned}
L(\xi,\mu,\beta) = R^2 - \sum_i (R^2 + \xi_i - \|\Phi(x_i) - a\|^2)\beta_i \\
- \sum_i \xi_i \mu_i + C \sum_i (\kappa[\boldsymbol{x}_i]\xi_i).
\end{aligned}
\tag{6}
$$

A definition of a problem specific differentiated confidence value for weighting has so far not been introduced. Liu et al. used the SVDD distance of a first training run as weighting for a second run. Here, we may later harness some a priori information for a more specific weighting.

In equation (6) the last term determines the trade-off between accepted error and hypersphere volume like the last term in equation (1). In contrast to the standard version equation (1), each point x_i is individually weighted according to its individual confidence of membership to the positive class by $\kappa[x_i]$. κ gives a measure for the reasonability of x_i.

We will later use this approach for modelling uncertainty in the use case of energy management. Beforehand we briefly discuss a specialized application for the SVDD model of feasible region: the ability to be used as decoder.

2.3 Decoders for Scheduling

In order to be able to systematically generate feasible solutions directly from the search space model, a decoder approach had been developed on top of the support vector model instead of merely telling feasible and infeasible schedules apart. In (Bremer and Sonnenschein, 2013) a so called support vector decoder has been introduced. Basically, a decoder is a constraint handling technique that gives an algorithm hints on where to look for feasible solutions. It imposes a relationship between a decoder solution and a feasible solution and gives instructions on how to construct a feasible solution (Coello Coello, 2002). For example, (Koziel and Michalewicz, 1999) proposed a homomorphous mapping between an n-dimensional hyper cube and the feasible region in order to transform the problem into a topological equivalent one that is easier to handle. In order to be able to derive such a decoder mapping automatically from any given energy unit model, (Bremer and Sonnenschein, 2013) developed an approach based on the mentioned support vector model (Bremer et al., 2011).

Provided the feasible region of an energy unit has been encoded by SVDD, a decoder can be derived as follows. The set of alternatively feasible schedules after encoding by SVDD is represented as pre-image of a high-dimensional sphere $\mathbb{S}$. Figure 2 shows the situation. 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 a ball and geometrically easier to handle with the following relations: If a schedule is feasible, i.e. can be operated by the unit without violating any technical constraint, it lies inside the feasible region (grey area on the left hand side in figure 2). Thus, the schedule 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 sphere. An infeasible schedule (e. g. $\boldsymbol{x}$ in Fig. 2) lies outside the feasible region and thus its image $\hat{\Psi}_x$ lies outside the ball. But, some important relations are known: the center of the ball, the distance of the image from the center and the radius of the ball. One can now move the image of an infeasible schedule along the difference vector towards the center until it touches the ball. Finally, the pre-image of the moved image $\tilde{\Psi}_x$ is calculated to get a schedule at the boundary of the feasible region: a repaired schedule $\boldsymbol{x}^*$ that is now feasible. No mathematical description of the original feasible region or of the constraints are needed to do this. More sophisticated variants of transformation are e. g. given in (Bremer and Sonnenschein, 2013).

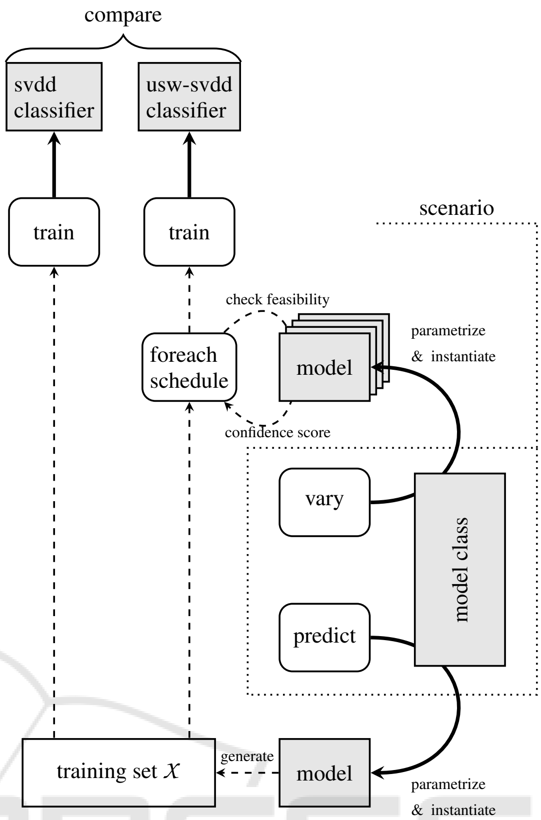

Figure 3: Integration of confidence scores and evaluation scheme for comparing both classifiers.

3 MODELING CONFIDENCE

In order to model the uncertainty in a schedule's operability we define the confidence of a schedule as the share of variations of the initial state that still allows operating the schedule without any modification. Let $\mathcal{X}$ be a set of d-dimensional schedules $\boldsymbol{x}_i$ that is going to serve as training set for building the SVDD model. $\mathcal{X}$ has been generated by assuming operation of a unit U starting from an initial operation state $z_0 \in \boldsymbol{Z}_U$ at a certain future point in time with the set $\boldsymbol{Z}_U$ of all possible operation states. This set is unit specific. To give an example, $\boldsymbol{Z}_U$ in the case of a co-generation plant might be in the simplest version the set of assignments for the state of charge (SOC) of an associated thermal buffer store. Let $\Omega(z_0)$ bet a set of variations of z_0 and $\mathcal{F}[\Omega(z_0)]$ the set of schedules $\boldsymbol{x}_i \in \mathcal{X}$ that are operable from any state in $\Omega(z_0)$ without modification. We now define the confidence of a schedule $\boldsymbol{p} \in \mathcal{X}$ as the ratio

$$\begin{aligned}\kappa[\boldsymbol{p}] &= P(\boldsymbol{p} \in \mathcal{F}[\Omega(z_0)] | \boldsymbol{p} \in \mathcal{F}[z_0]) \\ &= \frac{|\{\boldsymbol{x} | \boldsymbol{x} \in \mathcal{F}[z] \forall z \in \Omega(z_0)\}|}{|\Omega(z_0)|}.\end{aligned} \quad (7)$$

Table 1: Improved classification for a boiler with different water drawing profiles and different variations in usage prediction.

	draught w_1		draught w_2		draught w_3		
σ / kJ	SVDD	csw-SVDD	SVDD	csw-SVDD	SVDD	csw-SVDD	$\overline{\Delta}$ / %
135	0.313 ± 0.341	0.513 ± 0.381	0.281 ± 0.324	0.501 ± 0.372	0.308 ± 0.339	0.505 ± 0.384	74,37
90	0.527 ± 0.341	0.674 ± 0.319	0.532 ± 0.340	0.699 ± 0.298	0.527 ± 0.341	0.674 ± 0.319	30.24
45	0.841 ± 0.190	0.904 ± 0.149	0.860 ± 0.187	0.918 ± 0.120	0.841 ± 0.190	0.904 ± 0.149	6.99
27	0.943 ± 0.085	0.965 ± 0.072	0.949 ± 0.081	0.969 ± 0.066	0.943 ± 0.085	0.965 ± 0.072	2.15
18	0.969 ± 0.053	0.981 ± 0.048	0.973 ± 0.047	0.984 ± 0.038	0.970 ± 0.053	0.981 ± 0.048	0.91

In this way, the confidence is the probability of still being operable if a given variation is applied to the initial operation state that had been taken as assumption for generating the training set of feasible schedules.

What remains open is the definition of variation in initial states. The actual design of such variation highly depends on the unit type at hand and on its embedding into the actual operation site. For this reason, this question cannot be answered in general here. In this paper we define variation for our simulations in a scenario specific way.

By using equation (6) instead of equation (1) in the SVDD part of the surrogate model for the feasible regions of energy units (and for the derived decoder) and by using the expectation value of the feasibility of a schedule under changed conditions for the units operations as defined in (7) as a score for the confidence of the schedule, we define the confidence score weighted extension to the surrogate model (csw-SVDD) used in (Bremer et al., 2011).

4 RESULTS

We tested the approach with a simulation study. For this purpose we used appliances with a characteristics that allows for a well defined simulated variation in initial operation state. We have chosen an under-counter water boiler, a co-generation plant and a fridge as example units for electricity generation as well as demand. All models had already been used in several studies and projects for evaluation (Bremer et al., 2010; Bremer and Sonnenschein, 2013; Neugebauer et al., 2015; Hinrichs et al., 2013a; Nieße and Sonnenschein, 2013).

Fridge: A fridge allows for modelling different variations. We tested two variants: variations in changing the thermal mass and variation of the expected start temperature.

Co-generation: For co-generation plants (CHP) we modeled errors in expected weather conditions resulting in differences for the usage of the concurrently produced heat. Hence, we co-simulated CHP together with the heat losses of a house based on weather forecasts.

Water boiler: By keeping a water reservoir within a certain temperature range by an electrical heating device, electricity consumption can be scheduled with rather few constraints. Assuming the technical insulation setting as fixed, losses are merely dependent on the ambient temperature difference. On the other hand, possible variations in scheduling load depend on the predicted usage profile for water drawing. Setting the ambient temperature fixed, the initial state for scheduling is determined by the temperature of the water in the tank and the profile for predicted water drawing during the scheduling horizon. For variations, we modeled different prediction errors for the usage profile.

Table 2: Comparison of decoding errors as portion of correctly constructed schedules for different forecast deviations using the example of a boiler with predicted hot water demand.

σ / kJ	SVDD	csw-SVDD
9	0.074 ± 0.243	0.003 ± 0.056
18	0.350 ± 0.445	0.025 ± 0.152
27	0.524 ± 0.469	0.098 ± 0293
45	0.738 ± 0.411	0.594 ± 0.468
67.5	0.842 ± 0.355	0.804 ± 0.387

In order to evaluate the improvement of the modified model we trained two models with basically the same training set of feasible schedules generated from the simulation model of the unit which is also used for evaluation of both surrogates. Figure 3 shows the setting of the basic evaluation scenario.

Each scenario comprises a specific model class for an energy unit and a prediction for an initial state which serves as parametrization for instantiating a model of the energy unit. From this model a training set X of feasible schedules is generated. Each schedule consists of a fixed number d of values for consecutive mean real power at which the unit can be operated without violating any constraint. This training set serves for training a classic SVDD classifier surrogate model for testing feasibility of a given schedule without a need for the actual energy unit model. At the same time each scenario contains a unit specific definition of variation σ for the initial state. This variation is used to generate a set of models, each with a random variation. Each schedule in the training set is then checked for feasibility with each of these varied models. The expectation value of feasibility under a certain variety of initial operation states (given the schedule $\boldsymbol{x}$ was feasible under the fixed, predicted initial operation state) serves as confidence score $\kappa[\boldsymbol{x}]$ for training a csw-SVDD. Finally, both classifiers can be compared by using classical classifier evaluation methods (Powers, 2008; Witten et al., 2011). To evaluate the classifier performance, we calculated the confusion matrix by comparing classifier and the original model that had been used for generating the training set and derived standard indicators for comparison (Powers, 2011). Feasibility of a randomly (equally distributed) generated schedule is tested for feasibility once with help of the classifier and once with the help of the unit model. In each scenario, 10000 variations have been used to find the expectation value κ.

Table 1 shows some results for a water boiler. In this scenario we estimated a given water profile for hot water drawing as predicted usage. Hot water usage strongly determines feasibility of a given electrical profile. As variations we generated random deviations from the given water profile of a given size by adding normally distributed values with given standard deviation σ (negative drawings were corrected to zero for plausibility) ranging from 18 to 135 kJ per 15 minute time interval. We tested scenarios with a duration of one hour with a 15 minute resolution and the following artificial drawing profiles: $w_1 = (180\,\text{kJ}, 0\,\text{kJ}, 0\,\text{kJ}, 720\,\text{kJ})$, $w_2 = (0\,\text{kJ}, 1440\,\text{kJ}, 180\,\text{kJ}, 540\,\text{kJ})$ and $w_3 = (180\,\text{kJ}, 90\,\text{kJ}, 90\,\text{kJ}, 180\,\text{kJ})$.

The absolute performance (depicted is the recall value) degrade fast with growing uncertainty in both classifiers. This is as expected because of the growing deviation from the expected initial state. Nevertheless, the csw-SVDD performs better in all cases and the mean relative improvement and thus the advantage grows with growing error in prediction. Table 2 shows the results (error rate of not correctly generated schedules) for a decoder built from the respective classifier for profile 3 only. The results for the decoder part are not as good as for the classifier model part but nevertheless significant.

For evaluating the classifiers we primarily use the recall indicator. The precision degrades in both cases significantly. This is immediately apparent. The precision reflects the likelihood of a found schedule being feasible (Powers, 2011). Because feasibility here is checked under changed preconditions and feasibility is a property of the schedules, precision degrades in both classifiers at approximately the same level. The new csw-SVDD classifier for energy resources surrogate modeling shows but a higher recall behavior, because the recall reflects the likelihood of a schedule being feasible even under changed conditions. But this is exactly what is needed for the use case of checking feasibility of a schedule during energy management operations.

Table 3: Comparison of classifier recall indicators (higher values are better) for further scenarios.

scenario	SVDD	csw-SVDD
fridge 1	0.927 ± 0.045	0.994 ± 0.025
fridge 2	0.747 ± 0.028	0.829 ± 0.085
chp	0.838 ± 0.260	0.884 ± 0.226

Table 4: Comparison of classifier accuracy for a simulated boiler with 24-dimensional schedules and deviations (σ) in predicted water usage of different size in a different number of time intervals.

σ, n	SVDD	csw-SVDD
60, 3	0.8431 ± 0.0939	0.9371 ± 0.0966
120, 1	0.8644 ± 0.1323	0.9507 ± 0.1051
120, 2	0.6802 ± 0.2196	0.9372 ± 0.1062
120, 3	0.5175 ± 0.2658	0.9027 ± 0.1291

Table 3 shows some further results for a 2 hour time frame. For fridge 1 an unpredictable user interaction was simulated by adding a random thermal mass (30 ± 5 kJ, equating to about 500 g of food with room temperature) to the reefer cargo in the fridge. For fridge 2 a variation of the predicted starting temperature was introduced. In the CHP scenario the thermal demand was varied to simulate a deviation from the weather forecast.

Finally, table 4 shows some results for longer time periods with 24-dimensional schedules. Again, these are boilers with variations in a limited number of n time periods. Due to a lack of real world data, a normal distribution of the variations has been assumed in all simulations according to (Stadler, 2005). This assumption is likely to become invalid in practice. An advantage of the chosen approach for the csw-SVDD surrogate is the ability to derive the decision boundary unsupervised from the confidence scores of the individual schedules in the training set regardless of the underlying distributions. In this way, the approach can be used unchanged for individual variations of newly implemented and integrated energy resource models; even if they are introduced later at run time.

5 CONCLUSION

Predictive energy management for balancing or planning electricity demand and production according to operation schedules needs predictions of future operation alternatives and thus information about flexibilities of all devices for the scheduler to choose from. Such predictions on flexibility found meta-models as representations of individually restricted search spaces. Whether such a predicted operation schedule is actually still operable when it comes to finally operating the assigned (optimal) ones depends on several certain predictions that where made while constructing the training set of probably feasible schedules.

A robust planning algorithm should take into account this uncertainty of operability already during the phase planning. For the use case scrutinized in this contribution, robustness of a schedule is defined by the operability even under changed circumstances and preconditions. This ability of a schedule is condensed into a confidence value that allows individual weighting during the training phase of the search space meta-model.

To achieve this goal, we adapted an approach for confidence integration in classification, added a confidence model specific for electric flexibilities for operation schedules, and demonstrated its applicability with several use cases. The results are already promising for the model part and call for further extension especially regarding concrete definitions of variety and confidence for specific unit types.

Future work will have to target a better integration of uncertainty into decoders as well. If this is achieved, a more robust scheduling within virtual power plants will lead to a better support for the integration of fluctuating renewable resources. For the case of surrogate modelling this was already improved with the approach proposed here.

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REFERENCES

Alharbi, W. and Raahemifar, K. (2015). Probabilistic coordination of microgrid energy resources operation considering uncertainties. *Electric Power Systems Research*, 128:1 – 10.

Ben-Hur, A., Siegelmann, H. T., Horn, D., and Vapnik, V. (2001). Support vector clustering. *Journal of Machine Learning Research*, 2:125–137.

Blank, M. and Lehnhoff, S. (2014). Correlations in reliability assessment of agent-based ancillary-service coalitions. In *Power Systems Computation Conference (PSCC), 2014*, pages 1–7.

Braubach, L., van der Hoek, W., Petta, P., and Pokahr, A., editors (2009). *Towards Reactive Scheduling for Large-Scale Virtual Power Plants.*, volume 5774 of *Lecture Notes in Computer Science*. Springer.

Bremer, J., Andreßen, S., Rapp, B., Sonnenschein, M., and Stadler, M. (2008). A modelling tool for interaction and correlation in demand-side market behaviour. *New methods for energy market modelling*, pages 77–92.

Bremer, J., Rapp, B., and Sonnenschein, M. (2010). Support vector based encoding of distributed energy resources' feasible load spaces. In *IEEE PES Conference on Innovative Smart Grid Technologies Europe*, Chalmers Lindholmen, Gothenburg, Sweden.

Bremer, J., Rapp, B., and Sonnenschein, M. (2011). Encoding distributed search spaces for virtual power plants. In *IEEE Symposium Series on Computational Intelligence 2011 (SSCI 2011)*, Paris, France.

Bremer, J. and Sonnenschein, M. (2013). Constraint-handling for optimization with support vector surrogate models – a novel decoder approach. In Filipe, J. and Fred, A., editors, *ICAART 2013 – Proceedings of the 5th International Conference on Agents and Artificial Intelligence*, volume 2, pages 91–105, Barcelona, Spain. SciTePress.

Bremer, J. and Sonnenschein, M. (2014). Constraint-handling with support vector decoders. In Filipe, J. and Fred, A., editors, *Agents and Artificial Intelligence*, volume 449 of *Communications in Computer and Information Science*, pages 228–244. Springer Berlin Heidelberg.

Chang, W.-C., Lee, C.-P., , and Lin, C.-J. (2013). A revisit to support vector data description (svdd). technical report, Department of Computer Science, National Taiwan University, Taipei 10617, Taiwan.

Coello Coello, C. A. (2002). 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*, 191(11-12):1245–1287.

Coll-Mayor, D., Picos, R., and Garciá-Moreno, E. (2004). State of the art of the virtual utility: the smart distributed generation network. *International Journal of Energy Research*, 28(1):65–80.

GhasemiGol, M., Sabzekar, M., Monsefi, R., Naghibzadeh, M., and Yazdi, H. S. (2010). A new support vector data description with fuzzy constraints. In *Proceedings of the 2010 International Conference on Intelligent Systems, Modelling and Simulation*, ISMS '10, pages 10–14, Washington, DC, USA. IEEE Computer Society.

Hinrichs, C., Bremer, J., and Sonnenschein, M. (2013a). Distributed Hybrid Constraint Handling in Large Scale Virtual Power Plants. In *IEEE PES Conference on Innovative Smart Grid Technologies Europe (ISGT Europe 2013)*. IEEE Power & Energy Society.

Hinrichs, C., Sonnenschein, M., and Lehnhoff, S. (2013b). Evaluation of a Self-Organizing Heuristic for Interdependent Distributed Search Spaces. In Filipe, J. and Fred, A. L. N., editors, *International Conference on Agents and Artificial Intelligence (ICAART 2013)*, volume Volume 1 – Agents, pages 25–34. SciTePress.

Ilić, M. D. (2007). From hierarchical to open access electric power systems. *Proceedings of the IEEE*, 95(5):1060–1084.

Koziel, S. and Michalewicz, Z. (1999). Evolutionary algorithms, homomorphous mappings, and constrained parameter optimization. *Evol. Comput.*, 7:19–44.

Liu, B., Xiao, Y., Cao, L., Hao, Z., and Deng, F. (2013). Svdd-based outlier detection on uncertain data. *Knowledge and Information Systems*, 34(3):597–618.

Lukovic, S., Kaitovic, I., Mura, M., and Bondi, U. (2010). Virtual power plant as a bridge between distributed energy resources and smart grid. *Hawaii International Conference on System Sciences*, 0:1–8.

McArthur, S., Davidson, E., Catterson, V., Dimeas, A., Hatziargyriou, N., Ponci, F., and Funabashi, T. (2007). Multi-agent systems for power engineering applications – Part I: Concepts, approaches, and technical challenges. *IEEE Transactions on Power Systems*, 22(4):1743–1752.

Neugebauer, J., Kramer, O., and Sonnenschein, M. (2015). Classification cascades of overlapping feature ensembles for energy time series data. In *Proceedings of the 3rd International Workshop on Data Analytics for Renewable Energy Integration (DARE'15), ECML/PKDD 2015*. Springer.

Nieße, A., Beer, S., Bremer, J., Hinrichs, C., Lünsdorf, O., and Sonnenschein, M. (2014). Conjoint dynamic aggrgation and scheduling for dynamic virtual power plants. In Ganzha, M., Maciaszek, L. A., and Paprzycki, M., editors, *Federated Conference on Computer Science and Information Systems - FedCSIS 2014, Warsaw, Poland*.

Nieße, A., Lehnhoff, S., Tröschel, M., Uslar, M., Wissing, C., Appelrath, H.-J., and Sonnenschein, M. (2012). Market-based self-organized provision of active power and ancillary services: An agent-based approach for smart distribution grids. In *COMPENG*, pages 1–5. IEEE.

Nieße, A. and Sonnenschein, M. (2013). Using grid related cluster schedule resemblance for energy rescheduling - goals and concepts for rescheduling of clusters in decentralized energy systems. In Donnellan, B., Martins, J. F., Helfert, M., and Krempels, K.-H., editors, *SMARTGREENS*, pages 22–31. SciTePress.

Nikonowicz, Ł. B. and Milewski, J. (2012). Virtual power plants – general review: structure, application and optimization. *Journal of Power Technologies*, 92(3).

Park, J., Kang, D., Kim, J., Kwok, J. T., and Tsang, I. W. (2007). Svdd-based pattern denoising. *Neural Computing*, 19(7):1919–1938.

Powers, D. M. W. (2008). Evaluation evaluation. In *Proceedings of the 2008 Conference on ECAI 2008: 18th European Conference on Artificial Intelligence*, pages 843–844, Amsterdam, The Netherlands, The Netherlands. IOS Press.

Powers, D. M. W. (2011). Evaluation: From precision, recall and f-measure to roc., informedness, markedness & correlation. *Journal of Machine Learning Technologies*, 2(1):37–63.

Ramchurn, S. D., Vytelingum, P., Rogers, A., and Jennings, N. R. (2012). Putting the 'smarts' into the smart grid: A grand challenge for artificial intelligence. *Commun. ACM*, 55(4):86–97.

Rapp, B. and Bremer, J. (2012). Design of an event engine for next generation cemis: A use case. In Hans-Knud Arndt, Gerlinde Knetsch, W. P. E., editor, *EnviroInfo 2012 – 26th International Conference on Informatics for Environmental Protection*, pages 753–760. Shaker Verlag. ISBN 978-3-8440-1248-4.

Schölkopf, B. (1997). *Support Vector Learning*. Dissertation, Fachbereich 13 Informatik der Technischen Universität Berlin, Oldenbourg Verlag, München.

Schölkopf, B., Mika, S., Burges, C., Knirsch, P., Müller, K.-R., Rätsch, G., and Smola, A. (1999). Input space vs. feature space in kernel-based methods. *IEEE Transactions on Neural Networks*, 10(5):1000–1017.

Sri, M., Huld, T., Dunlop, E. D., Albuisson, M., Lefevre, M., and Wald, L. (2007). Uncertainties in photovoltaic electricity yield prediction from fluctuation of solar radiation. In *22nd European Photovoltaic Solar Energy Conference*.

Stadler, P. D.-I. I. (2005). *Demand Response: Nichtelektrische Speicher fr Elektrizittsversorgungssysteme mit hohem Anteil erneuerbarer Energien*. Habilitation, Fachbereich Elektrotechnik, Universitt Kassel.

Tax, D. M. J. and Duin, R. P. W. (2004). Support vector data description. *Mach. Learn.*, 54(1):45–66.

Wang, J., Botterud, A., Bessa, R., Keko, H., Carvalho, L., Issicaba, D., Sumaili, J., and Miranda, V. (2011). Wind power forecasting uncertainty and unit commitment. *Applied Energy*, 88(11):4014 – 4023.

Wildt, T. (2014). Modelling uncertainty of household decision – making process in smart grid appliances adoption. In *Behave Energy Conference*, Oxford, UK.

Witten, I. H., Frank, E., and Hall, M. A. (2011). *Data Mining: Practical Machine Learning Tools and Techniques*. Morgan Kaufmann, Amsterdam, 3 edition.

Wu, F., Moslehi, K., and Bose, A. (2005). Power system control centers: Past, present, and future. *Proceedings of the IEEE*, 93(11):1890–1908.

Zhang, J., Hodge, B.-M., Gomez-Lazaro, E., Lovholm, A., Berge, E., Miettinen, J., Holttinen, H., and Cutululis, N. (2013). *Analysis of Variability and Uncertainty in Wind Power Forecasting: An International Comparison*. Energynautics GmbH.

Zheng, E.-H., Yang, M., Li, P., and Song, Z.-H. (2006). Fuzzy support vector clustering. In Wang, J., Yi, Z., Zurada, J. M., Lu, B.-L., and Yin, H., editors, *ISNN (1)*, volume 3971 of *Lecture Notes in Computer Science*, pages 1050–1056. Springer.

Zio, E. and Aven, T. (2011). Uncertainties in smart grids behavior and modeling: What are the risks and vulnerabilities? how to analyze them? *Energy Policy*, 39(10):6308 – 6320. Sustainability of biofuels.