Active Learning for Model Abstraction*

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***Abstract*—Organizational structures such as hierarchies provide an effective means to deal with the increasing complexity found in large-scale energy systems that results from uncertainties in nature as well as computational efforts in scheduling. Abstraction-based methods provide a way to calculate a simpler behavior model to be used in optimization in lieu of a combination of a set of behavior models. In particular, functional dependencies over the combinatorial domain are approximated by repeatedly sampling input-output pairs and substituting the actual function by piecewise linear functions. However, if the selected input-output pairs are weakly informative, the resulting abstracted optimization problem introduces severe errors in quality as well as bad runtime performance. This problem is reminiscent of the task of selecting the next most informative input for supervised learning algorithms in case labeled input is rare. We therefore propose to apply methods from active learning based on decision trees for regression to search for informative input candidates to sample and present preliminary results that motivate further research.**

I. Hierarchical Distributed Energy Management

Future energy systems move from systems of relatively few centrally organized units providing most of the power demanded by consumers to many highly distributed units calling for manageable control mechanisms [1]. To deal with the resulting complexity in scheduling and controlling power plants in the face of uncertainties introduced by nature and technical deficiencies, hierarchical organizations that form autonomously can be employed [2]. Figure 2 illustrates these so-called autonomous virtual power plants (AVPP) that are related to the concept of dynamic virtual power plants [3]. To achieve a reduction of complexity in the optimization problem to be solved by the overall system, techniques are borrowed from model abstraction [4]. In particular, functional dependencies over a combinatorial input domain stemming from the aggregate of underlying agents are approximated by repeatedly sampling input-output pairs and substituting the actual function by piecewise linear functions [6].

In general, the problem to be solved constitutes a hierarchical resource allocation problem [5], where the resource to be allocated to a set of agents maps to their scheduled contributions in order to meet a predicted demand over a scheduling window consisting of finitely many time steps with a fixed resolution of 15 minutes. Agents have to act proactively, i.e., create schedules since they are subject to inertia and cannot be assumed to react fast enough in case of rapidly increasing (or decreasing) demand. We derive the minimal set of constraints from the physical requirements that power plants impose (see [7] for a discussion of the literature):

- a minimal and maximal power boundary
- discontinuity given the ability to be switched off
- functions limiting the possible change in production over a certain period of time.

The latter function might depend on the type of an agent as well as the current contribution. From these physical constraints, we abstract minimal and maximal contributions and switching on and off to a sorted list of *feasible intervals* L^t_a. A power plant a that is capable of being switched off or run between some boundaries $P_{\min}$ and $P_{\max}$ would then for instance be represented by $L^t_a = \langle [0,0], [P_{\min}, P_{\max}] \rangle$. To allow planning for inertia in a, we introduce functions $\overrightarrow{A}^{\min}_a$ and $\overrightarrow{A}^{\max}_a$ that return the minimum and maximum contribution in a following time step given the current contribution. In the simplest case—we consider a constant maximal change ΔP—these functions are defined as:

$$\overrightarrow{A}^{\min}_a(x) = \max\{P_{\min}, x - \Delta P\}$$
$$\overrightarrow{A}^{\max}_a(x) = \min\{P_{\max}, x + \Delta P\}$$

But of course, these functions can model richer systems than that, e.g., consider a hot or cold start-up [7], have a dependency on the current contribution, or rates of change that map combinatorially to the underlying agents [6]. In addition to that, cost functions κ_a return the minimal costs incurred for a certain contribution.

$$\begin{aligned}
\underset{S_a[t]}{\text{minimize}} \quad & \alpha_\Delta \cdot \Delta + \alpha_\Gamma \cdot \Gamma \qquad (1)\\
\text{subject to} \quad & \forall a \in \mathcal{A}_\lambda, \forall t \in \mathcal{W} : \exists [x,y] \in L^t_a : x \le S_a[t] \le y,\\
& \overrightarrow{A}^{\min}_a(S_a[t-1]) \le S_a[t] \le \overrightarrow{A}^{\max}_a(S_a[t-1])\\
& \text{with } \Delta = \textstyle\sum_{t\in\mathcal{W}} |S_{\mathcal{A}_\lambda}[t] - S_\lambda[t]|,\\
& \text{and } \Gamma = \textstyle\sum_{a\in\mathcal{A}_\lambda,\ t\in\mathcal{W}} \kappa_a(S_a[t])
\end{aligned}$$

We propose to solve it using an approach based on self-organization:

- A so-called "regio-central" approach: agents transfer models to their local supervisor who, at meso-level, centrally optimizes the allocation [6], [7]
- An auction-based decentralized approach [2]

II. Issues with Model Abstraction

However, if the selected input-output pairs are selected in a weakly informative way, the resulting abstracted optimization problem introduces severe errors in quality as well as bad runtime performance.

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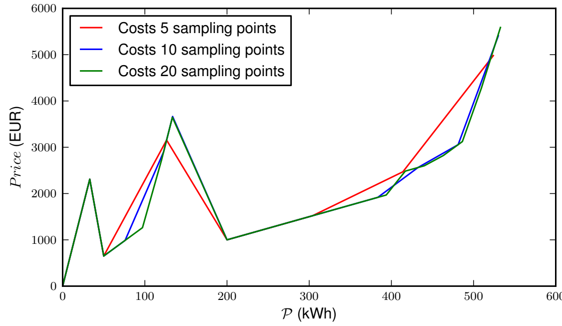
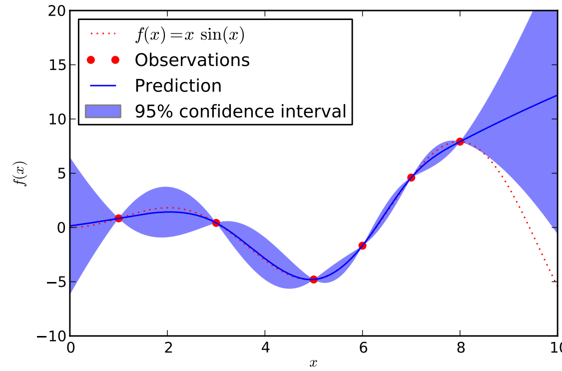


(a) Accuracy affected by the number of sampling points selected.



(b) A probabilistic regression model allows to quantify uncertainty at given points in the domain of a learned function.

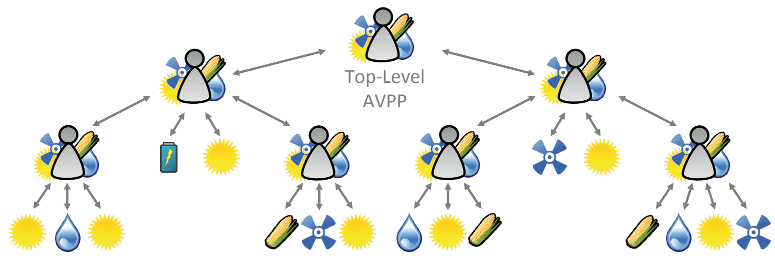


Fig. 2: Hierarchical system structure of a future autonomous power management system: Prosumers are structured into systems of systems represented by AVPPs acting as intermediaries, thereby decreasing the complexity of control and scheduling. AVPPs can be part of other AVPPs.

III. Improving Sampling Point Selection

IV. Evaluation

We investigate the effects of selecting a particular set of sampling points for one group that could have emerged as part of a self-organization process.

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