# 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 based on virtual power plants that form autonomously can be employed [2], [3]. Inner nodes of the hierarchy are called *autonomous* virtual power plants (AVPP) and act as intermediaries on behalf of their subordinate agents. Prosumers are thus structured into systems of systems represented by AVPPs, which can themselves can be part of other AVPPs, as shown in Fig. 1. 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 functions 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 $\mathcal{W}$ 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* $L_a^t$. 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 $L_a^t = \langle [0,0], [P_{\min}, P_{\max}] \rangle$. To allow planning for inertia in $a$, we introduce functions $\overrightarrow{A}_a^{\min}$ and $\overrightarrow{A}_a^{\max}$ 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 $\Delta P$—these functions are defined as:

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

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 $\kappa_a$ return the minimal costs incurred for a certain contribution.

We present the scheduling problem for some inner node—called intermediary $\lambda$—since the problem is solved top-down, as shown in Fig. 1. Each intermediary in turn redistributes its assigned fraction of the overall demand $S_\lambda[t]$ to its subordinate agents $\mathcal{A}_\lambda$ until all leaf agents, i.e., physical power plants, are assigned schedules. Note that the root node $\Lambda$ is assigned the actual total demand of the environment, i.e., $S_\Lambda[t] = A_{env}[t]$.

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

We propose to solve this problem using two approaches 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]

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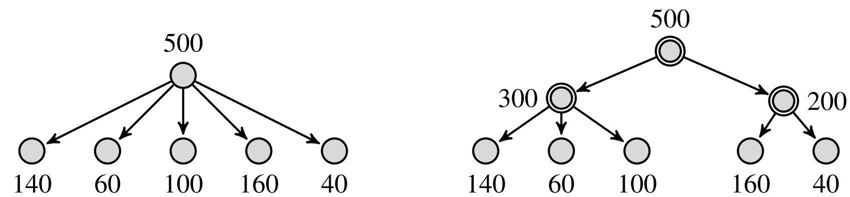


Fig. 1: Resource allocation problems can be solved using a hierarchical decomposition structure. Inner nodes representing intermediaries are marked by double circles.

- An auction-based decentralized approach [2]

In both cases, obtaining a good abstraction of an intermediary's behavior as a compact representation of the underlying set of subordinate agents is desirable.

## 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.

## 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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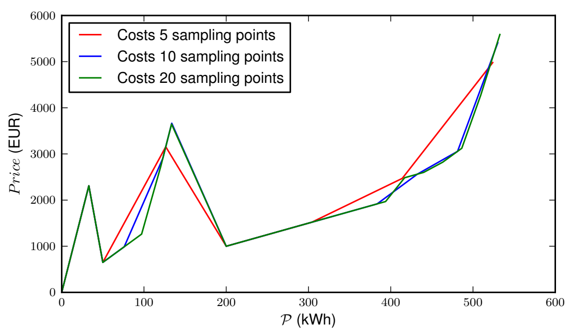
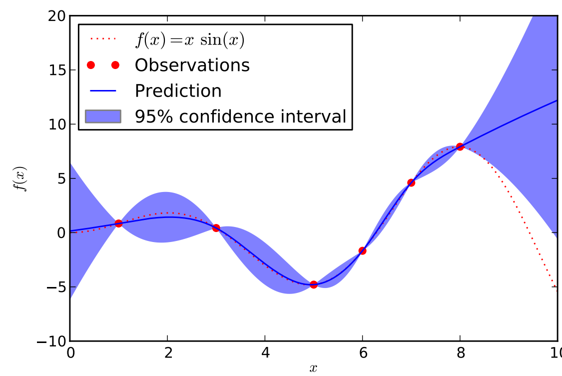



(a) Accuracy affected by the number of sampling points selected.




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