Active Learning for Abstract Models of Collectives

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fertilized forests

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Motivation

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- Adaptive systems used in resource-intensive domains
  - Unit commitment in virtual power plants (Schiendorfer et al., 2014)
  - Load balancing
- Efficient algorithms for resource allocation central to business processes
  - Discrete Optimization
  - Constraint/Mathematical Programming
  - ...
- Hierarchical decomposition desired
  - Abstraction based on *sampling* points of a collective
  - Which sampling points to select?

Resource Allocation Problems (RAP)

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General resource allocation (Van Zandt, 1995)

- One homogeneous resource – the *demand* x_R (continuous or discrete)
- e.g., Energy, Computing Resources (CPU time required for a job), Technical parts to be produced, in our model ...
- Provided by several agents x_i at different costs

$$\underset{\langle x_1,\ldots,x_n\rangle}{\text{minimize}} \quad \sum_{i=1}^{n} c_i(x_i) \quad \text{subject to} \quad \sum_{i=1}^{n} x_i = x_R$$

How to calculate the solution?

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Variation of general resource allocation

- Demand is given for a time frame $\mathcal{T}$
- Agents are subject to constraints such as minimal or maximal rates and *inertia*
- Cost function per plant, per production level

$$
\begin{aligned}
\underset{\mathcal{P}}{\text{minimize}} \quad & \sum_{t \in \mathcal{T}} \sum_{a \in \mathcal{A}} \kappa(\mathcal{P}_t^a) \\
\text{subject to} \quad & \forall a \in \mathcal{A}, t \in \mathcal{T} : \\
& \exists [x, y] \in L^a : x \leq \mathcal{P}_t^a \leq y, \\
& \sum_{t \in \mathcal{T}} |\mathcal{D}_t - \sum_{a \in \mathcal{A}} \mathcal{P}_t^a| \\
& [\ldots]
\end{aligned}
$$

How to solve this RAP?

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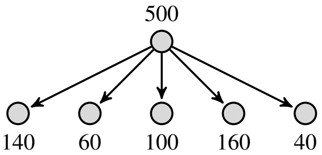
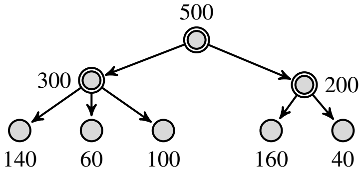
Constraint-Satisfaction-Optimisation-Problem (CSOP)

- Declarative and *versatile* approach for combinatorial problems
- Specify problem in terms of *variables*, *domains* and *constraints*
- Solve with Mixed-Integer-Programming (MIP), Linear Programming (LP), Constraint Programming (CP), etc.

Scalability issues with increasing numbers of agents!

Hierarchical System Structures



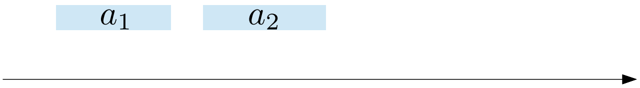


- Example: Unit Commitment in Power Management
- Energy offered by Suppliers
- Providers are organized hierarchically in *virtual power plants*)
  - Scalability benefits
  - Local uncertainty compensation mechanisms (scenarios, robust optimization (Anders et al., 2014))
- Abstraction reduces the complexity of the model of a collective's behavior

Abstraction

- Frame feasible regions: Find the corners and holes of the production space of a whole collective.
  - Done by means of interval arithmetics
  - Propagate to upper levels
- Approach based on sampling
  - Assume functional relationships
  - Approximation by iterated solving of slightly modified optimization problems and collecting input-output pairs *("Sampling")*
  - Using this approximation on higher levels

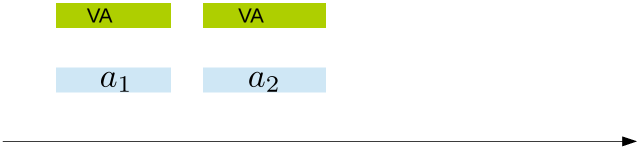
General Abstraction – Intuition



Possible production

$a_1 = \{[0,0],[1,4]\}, a_2 = \{[0,0][7,10]\}$

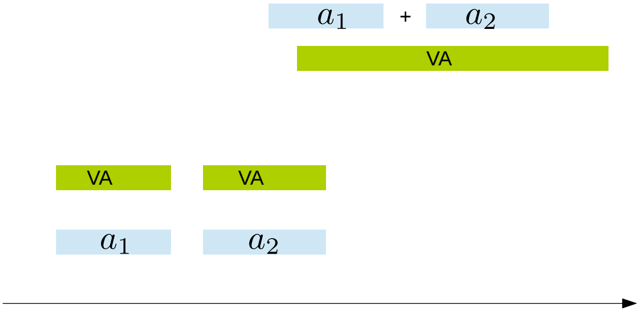
General Abstraction – Take individuals



Possible production

$\text{VA} \supset \{[0,0],[1,4],[7,10]\}$

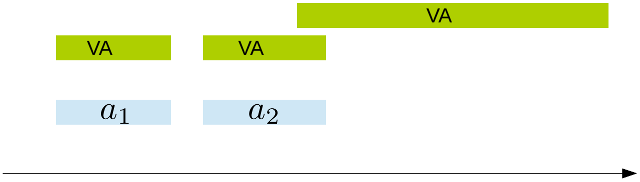
General Abstraction – Combine



Possible production

$[1, 4] \oplus [7, 10] = [8, 14]$

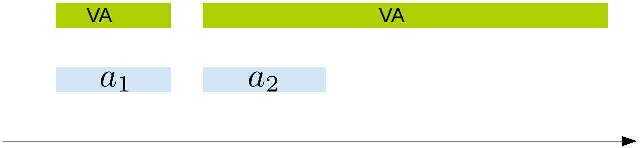
General Abstraction – Possible Overlaps



Possible production

$\mathrm{merge}(\{[0,0],[1,4],[7,10]\} \cup \{[8,14]\})$

General Abstraction – Merge



Possible production

$\text{merge}(\{[0,0],[1,4],[7,10]\} \cup \{[8,14]\}) = \{[0,0],[1,4],[7,14]\}$

Data collection

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1. Solve for *minimize* costs, given that the combined production is 0

   obtained by $e_{vp} = \underbrace{e_{bm}}_{0} + \underbrace{e_{hy}}_{0}$, costs: 0

2. Solve for *minimize* costs, given that the combined production is 50

   obtained by $e_{vp} = \underbrace{e_{bm}}_{25} + \underbrace{e_{hy}}_{25}$, costs: 400

3. Solve for *minimize* costs, given that the combined production is 55

   obtained by $e_{vp} = \underbrace{e_{bm}}_{35} + \underbrace{e_{hy}}_{20}$, costs: 550

4. $\cdots$

Approximation with piecewise linear functions

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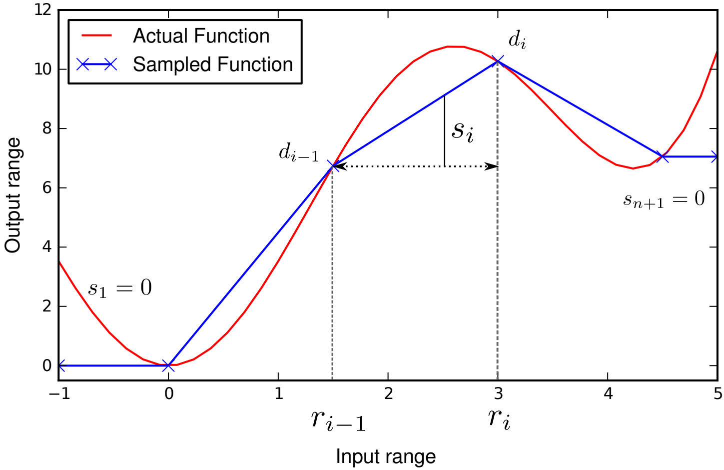

An example

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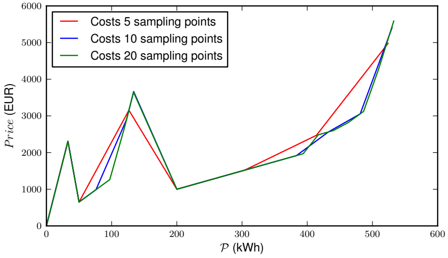
$$L_p = \langle [0,0], [50,100] \rangle, \qquad \kappa^p = 13$$
$$L_q = \langle [0,0], [15,35] \rangle, \qquad \kappa^q = 70$$
$$L_r = \langle [0,0], [200,400] \rangle, \qquad \kappa^r = 5$$

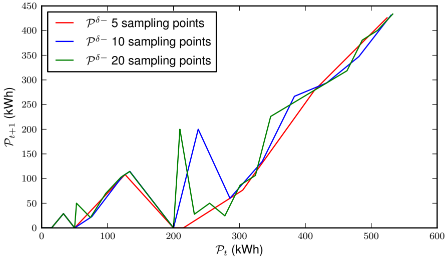
Three power plants p, q, and r controlled by an intermediary; costs are linear coefficients κ^i.

General abstraction yields feasible regions:

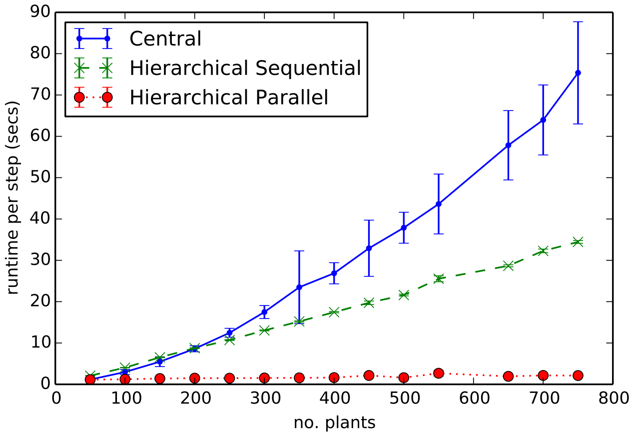
$$\langle [0,0], [15,35], [50,135], [200,535] \rangle$$

Sampling Abstraction – Visualised



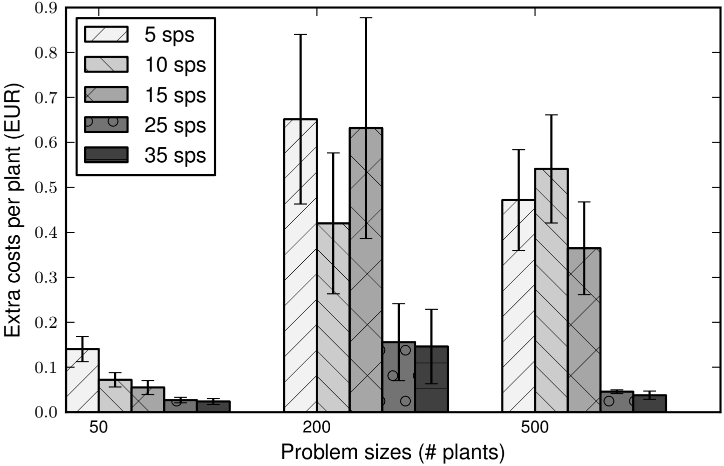


It's all fun and games . . .



Mean runtimes hierarchical vs. central

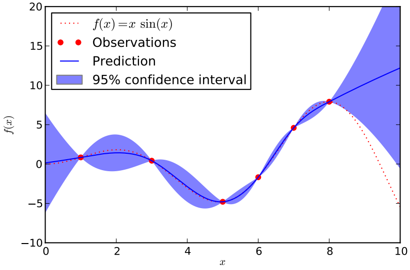
. . . until someone gets hurt



Only using more sampling points does not guarantee to increase accuracy!

Approach

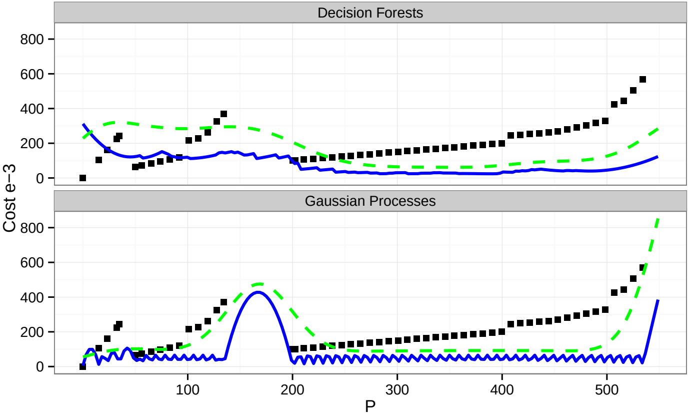
Apply *active learning* techniques (Settles, 2010): A learning algorithm chooses the next input to be labeled.



We investigated two regressors offering probabilistic estimates

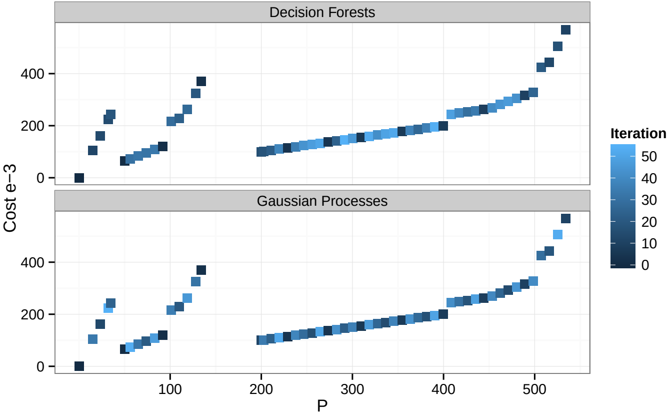
- Gaussian Processes (GPy)
- Decision Forests (Lassner and Lienhart, 2015)

Results I



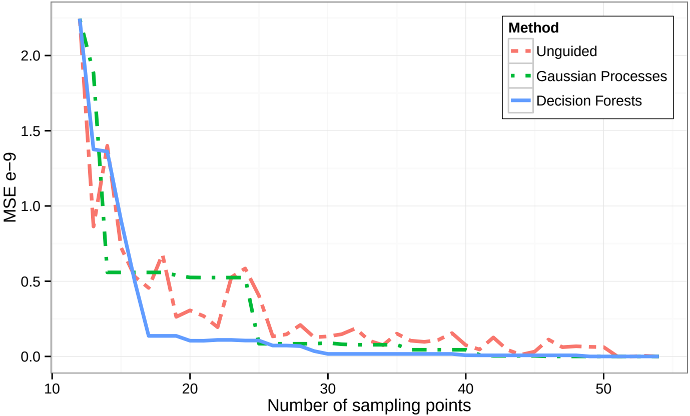
Query point selection by the two evaluated methods.

Results II



Point selection order: The lighter the point color, the later it was selected by the algorithm.

Results III



The mean MSE (scaled with 10^{-9}) for the entire trace is 0.28 (unguided), 0.26 (GP-guided) and 0.18 (DF-guided).

Future and ongoing work

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- Apply technique to other sampled functions
- Integrate the informed selector into the overall simulation/optimization algorithm
- Investigate other AL techniques
- Integrate domain-specific knowledge to improve the selection

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