Automatic Algorithm Configuration based on Local Search

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Motivation for automatic algorithm configuration

- Want to design 'best' algorithm to solve a problem
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  - Many test instances needed to generalize
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  - Many test instances needed to generalize
  - Many runs per instance needed for randomised algorithms
- Algorithm configuration / tuning still often done manually, using ad-hoc methods
  - $\rightsquigarrow$ tedious and time-consuming, sub-optimal results
  - $\rightsquigarrow$ big incentive for automation

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- Problems:
  - default settings $\rightsquigarrow \approx$ 300 seconds / run
  - good performance on a few instances may not generalise

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- Choose a "representative" benchmark set for tuning
- Perform iterative manual tuning:

start with some parameter configuration
repeat
  modify a single parameter
  if *results on tuning set improve* **then**
    keep new configuration
until *no more improvement possible (or "good enough")*

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Solution:

- automate process
- use more powerful search method

Related work

- Search approaches
  [Minton 1993, 1996], [Hutter 2004], [Cavazos & O'Boyle 2005], [Adenso-Diaz & Laguna 2006], [Audet & Orban 2006]

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- Stochastic Optimisation [Kiefer & Wolfowitz 1952], [Spall 1987]
- Learning approaches
  - Regression trees [Bartz-Beielstein et al. 2004]
  - Response surface models, DACE
    [Bartz-Beielstein et al. 2004–2006]
- Lots of work on per-instance / reactive tuning
  $\rightsquigarrow$ orthogonal to the approach followed here

Outline

1. Introduction
2. Iterated local search over parameter configurations
3. The FocusedILS algorithm
4. Sample applications and performance results
5. Conclusions and future work

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- with probability $p_{restart}$ randomly pick new θ

$\rightsquigarrow$ performs **biased random walk over local minima**

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- perturbation: change 3 randomly chosen parameters
- acceptance criterion: always select *better* configuration
- initialisation: pick *best* of default + R random configurations

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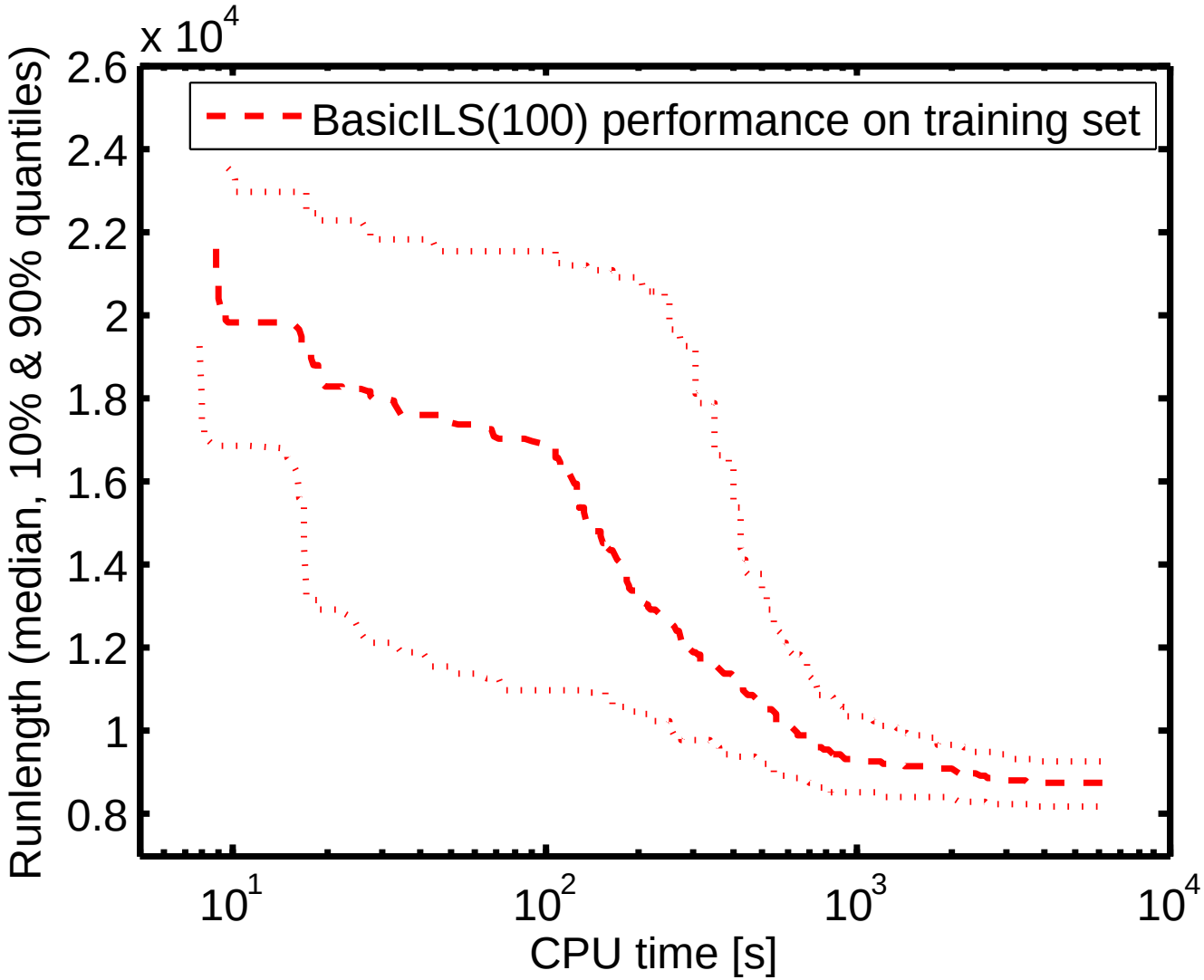
- Note: For large N, $\hat{c}_N(\theta)$ approaches true cost $c(\theta)$

Solution quality over time achieved by ParamILS



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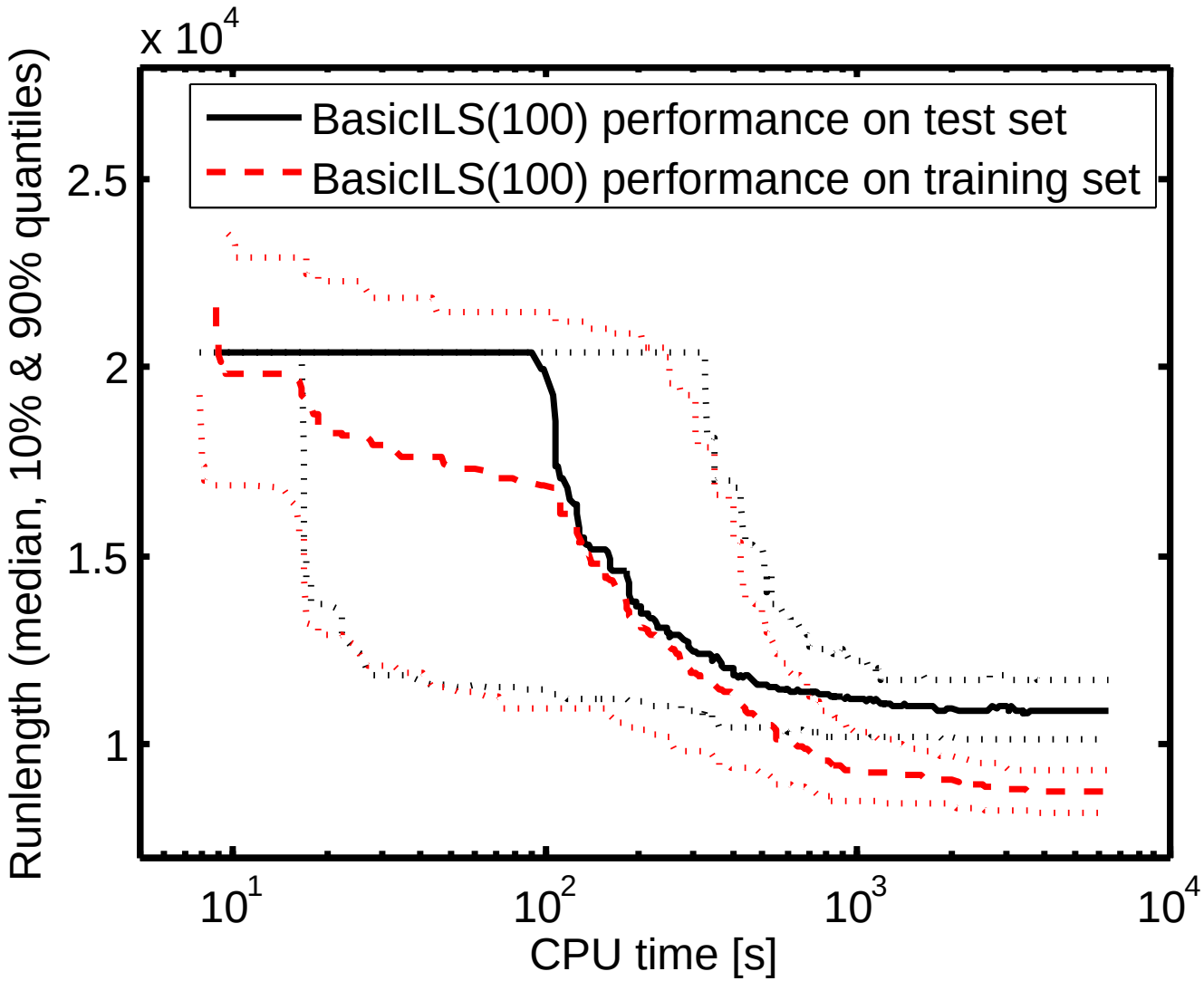
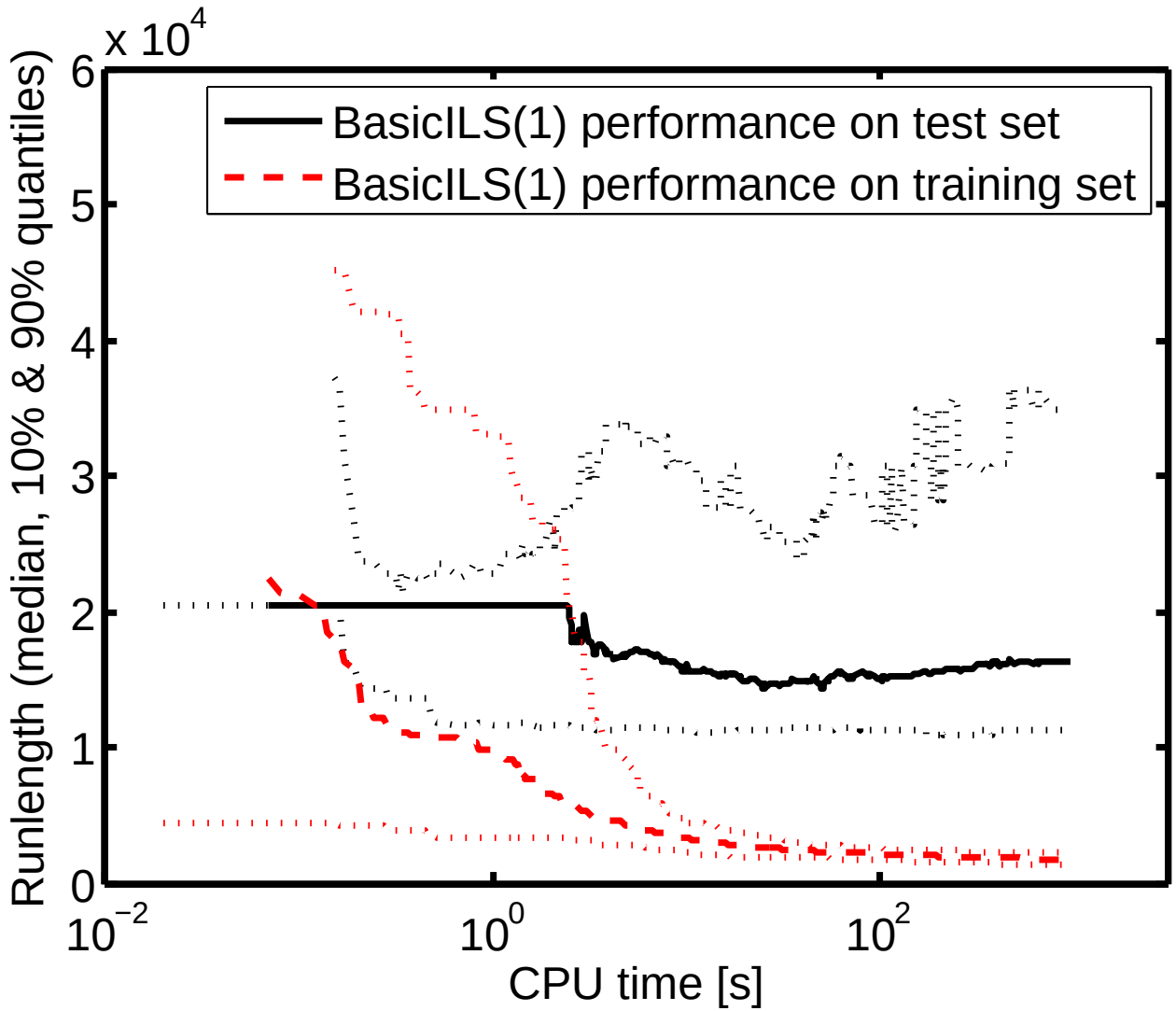
  - $\rightsquigarrow$ evaluating a configuration is very expensive
  - $\rightsquigarrow$ optimisation process is very slow
- too few
  - $\rightsquigarrow$ very noisy approximations $\hat{c}_N(\theta)$
  - $\rightsquigarrow$ poor generalisation to independent test runs

Generalisation to independent test runs (1)



Generalisation to independent test runs (2)



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- **Idea:** Use high $N(\theta)$ only for good θ
  - start with $N(\theta) = 0$ for all θ
  - increment $N(\theta)$ whenever θ is visited
  - additional runs upon finding new, better configuration θ

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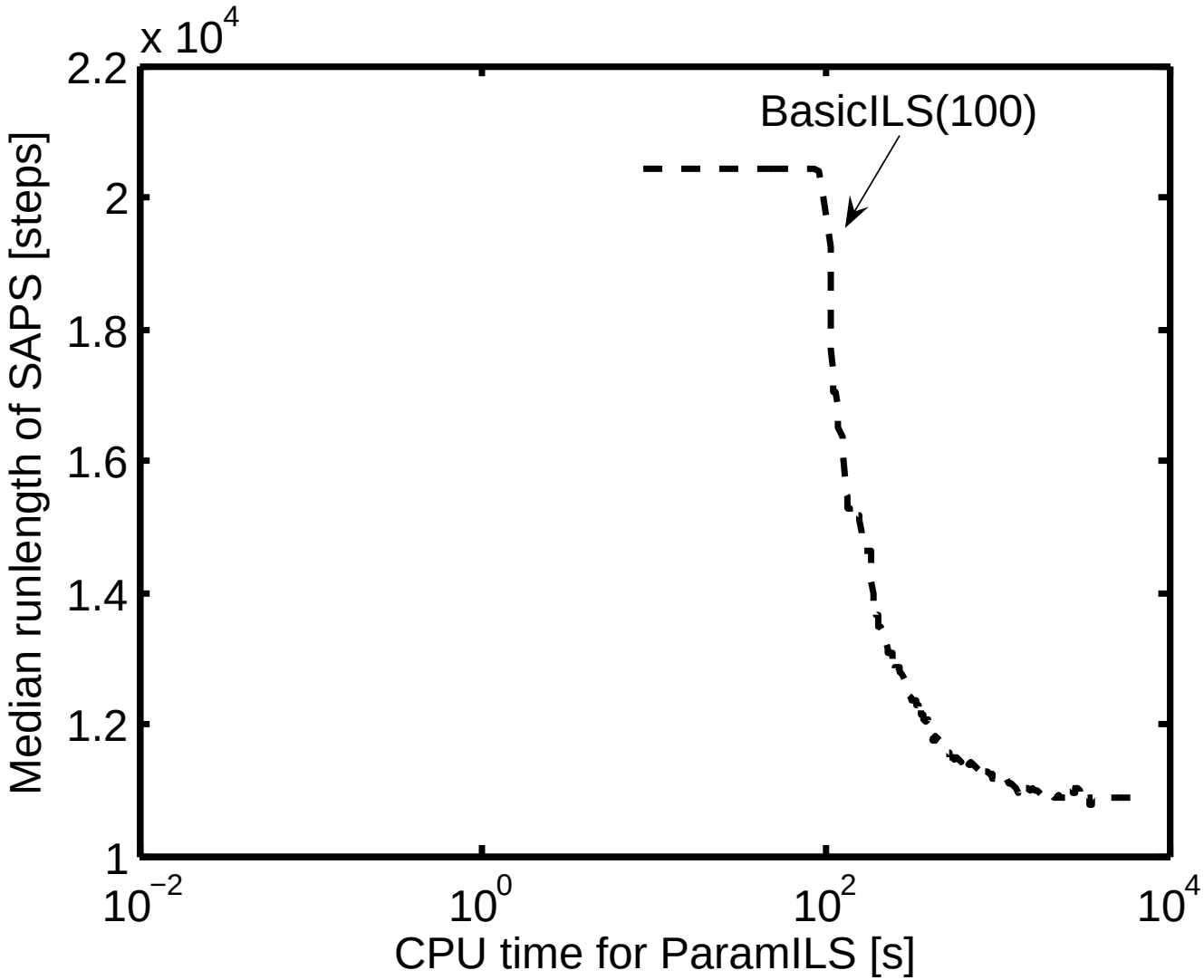
Key ideas in proof:

1. For $N(\theta), N(\theta') \rightarrow \infty$, comparisons between θ, θ' become precise.
2. Underlying ILS eventually reaches any configuration θ.

Performance of FocusedILS vs BasicILS

(Test performance on SAPS-QWH)



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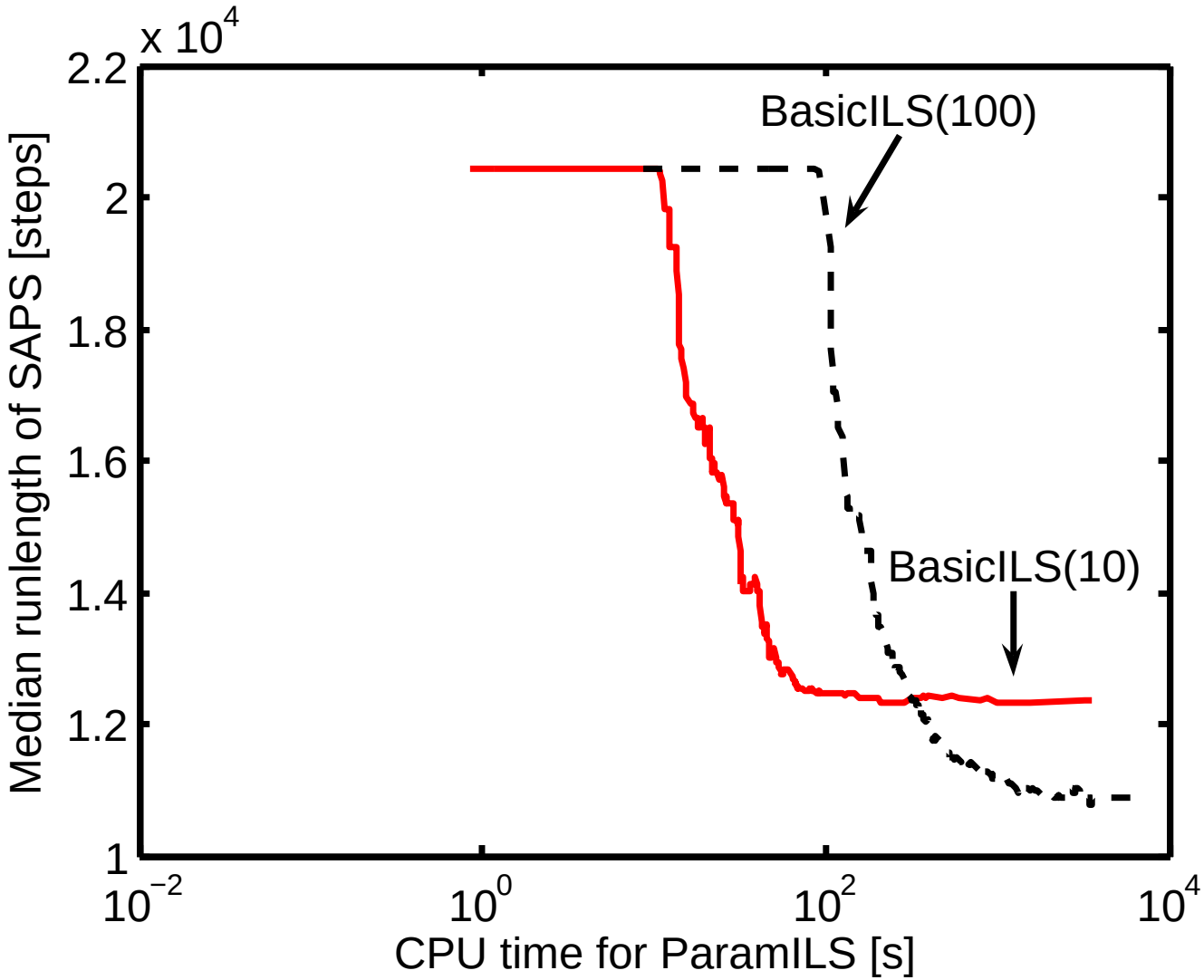

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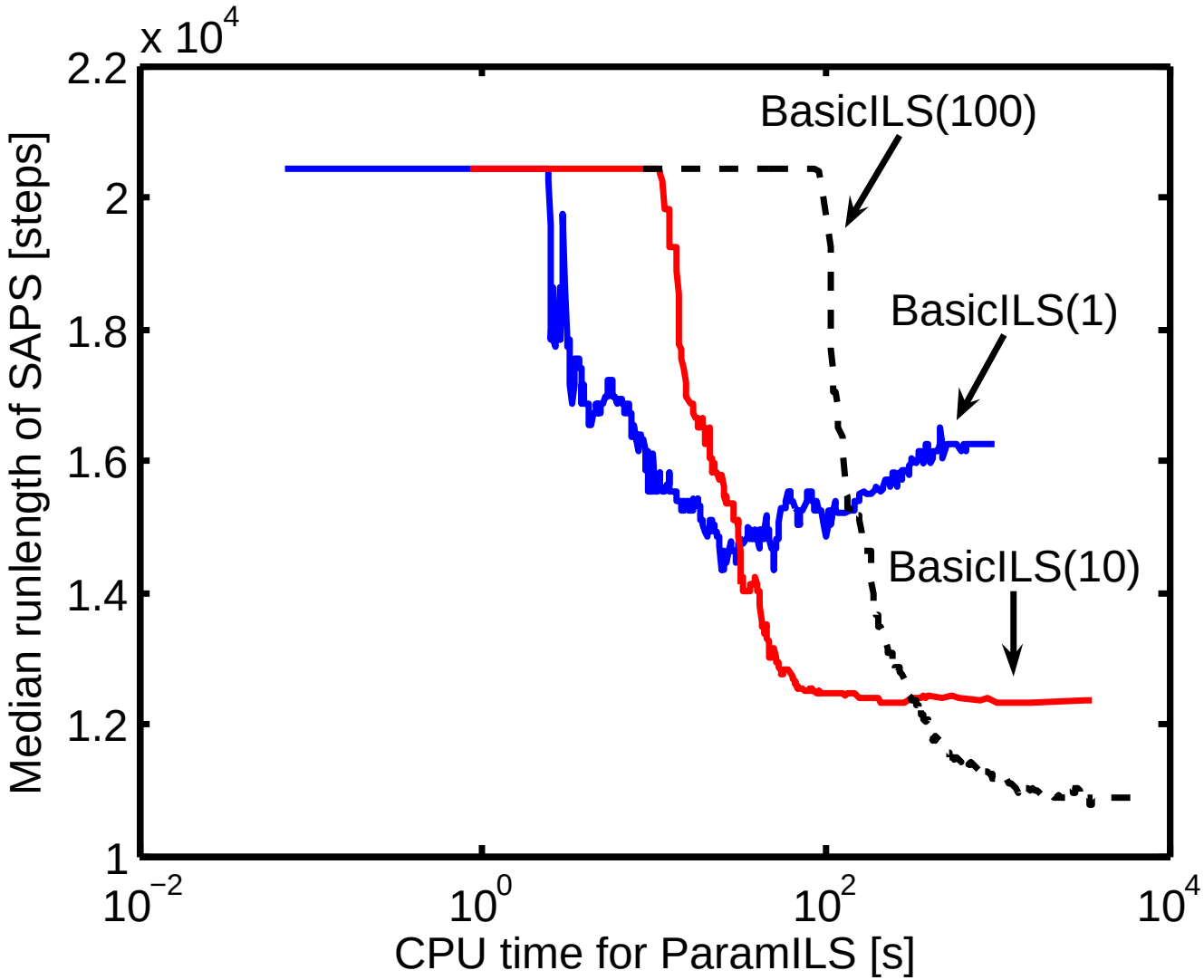

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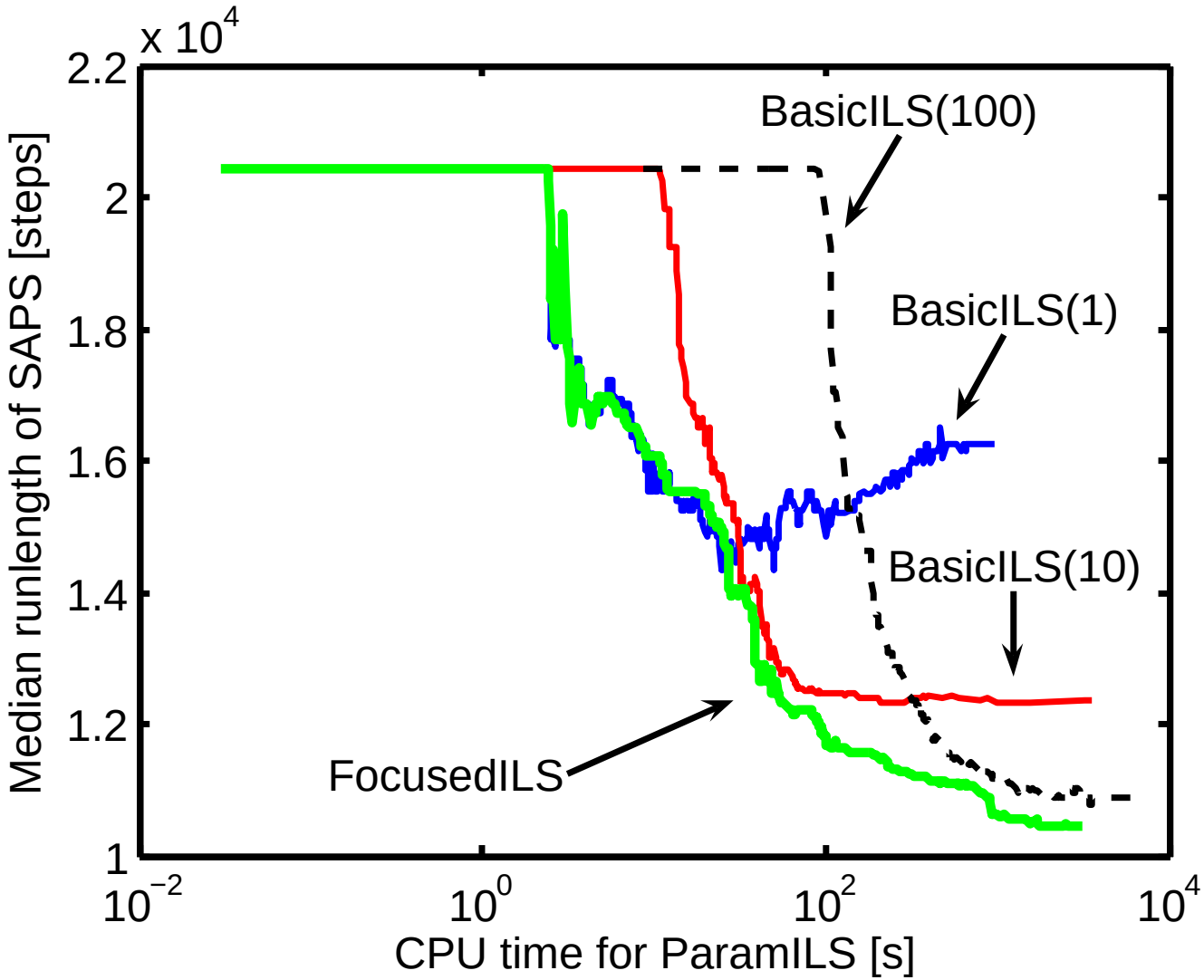

Sample applications and performance results

Experiment: Comparison to CALIBRA

Scenario	Default	CALIBRA(100)	BasicILS(100)	FocusedILS
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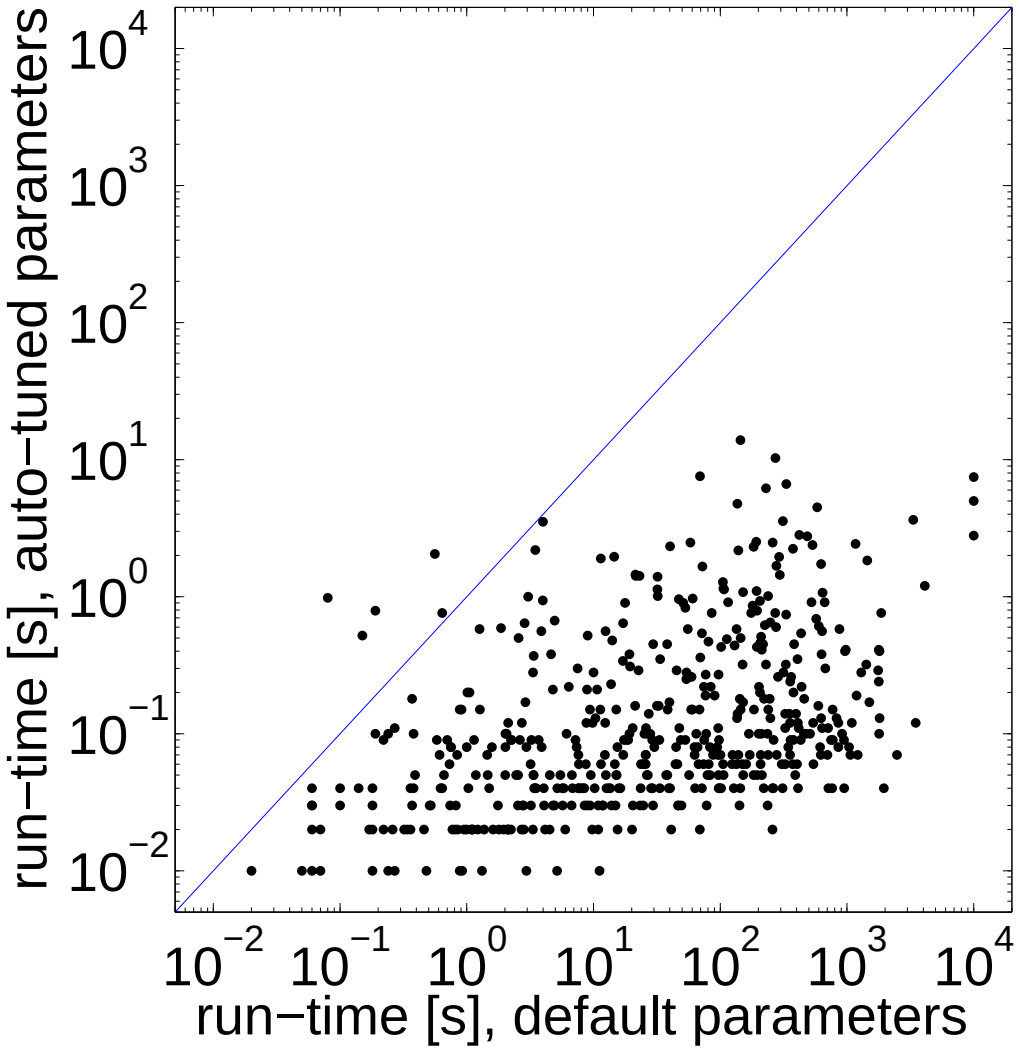
SAPS-SW	5.60 s	0.053 ± 0.010	0.046 ± 0.01	$\mathbf{0.043 \pm 0.005}$
SAT4J-SW	7.02 s	(too many param.)	1.19 ± 0.58	$\mathbf{0.65 \pm 0.2}$

Speedup obtained by automated tuning

(SAPS default *vs* tuned on test set SW-GCP)



Two 'real-world" applications

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  - 26 parameters
  - Software verification: 500-fold speedup
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- New replica exchange Monte Carlo algorithm for protein structure prediction
  - 3 parameters
  - 2-fold improvement
  - ⇝ New state of the art for 2D/3D protein structure prediction
  - ⇝ Thachuk, Shmygelska & Hoos (under review)

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  `http://www.cs.ubc.ca/labs/beta/Projects/ParamILS`

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