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# Shift Minimisation Personnel Task Scheduling Problem

**Andreas Ernst, CSIRO**

**Mohan Krishnamoorthy & Davaatseren Bataar, Monash University**

**Integer Programming Down Under, July 2011**



# Overview

- Problem Definition
- Motivation
  - Planes, Trains & Automobiles
- ILP formulation and exact algorithms
- Lagrangian Heuristics
- Results
- Conclusions

$$(-1)^m \frac{d^m}{dt^m} \geq 0, \quad m=1, 2, \dots$$

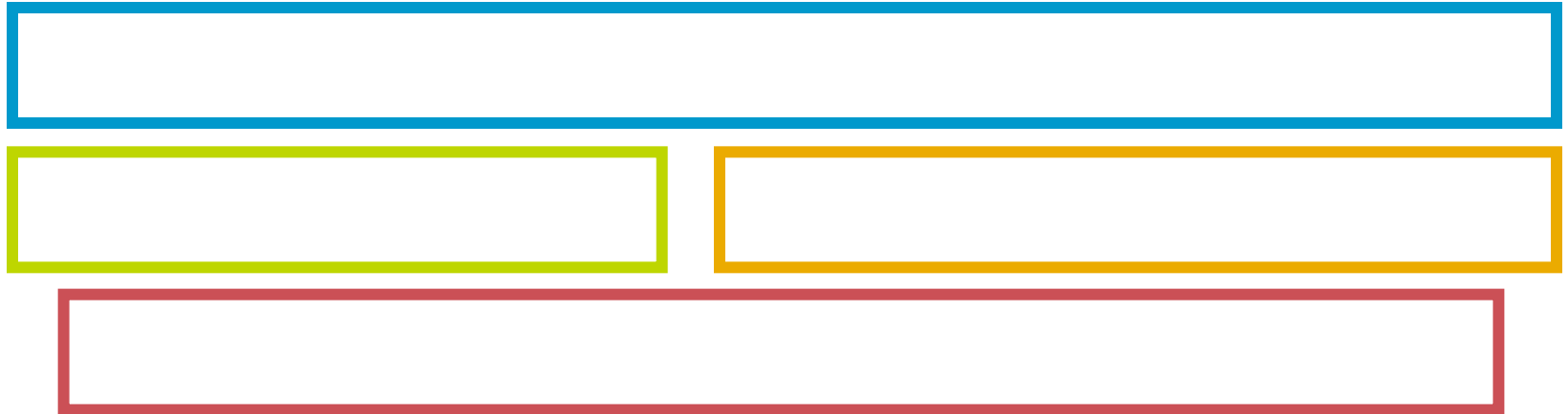
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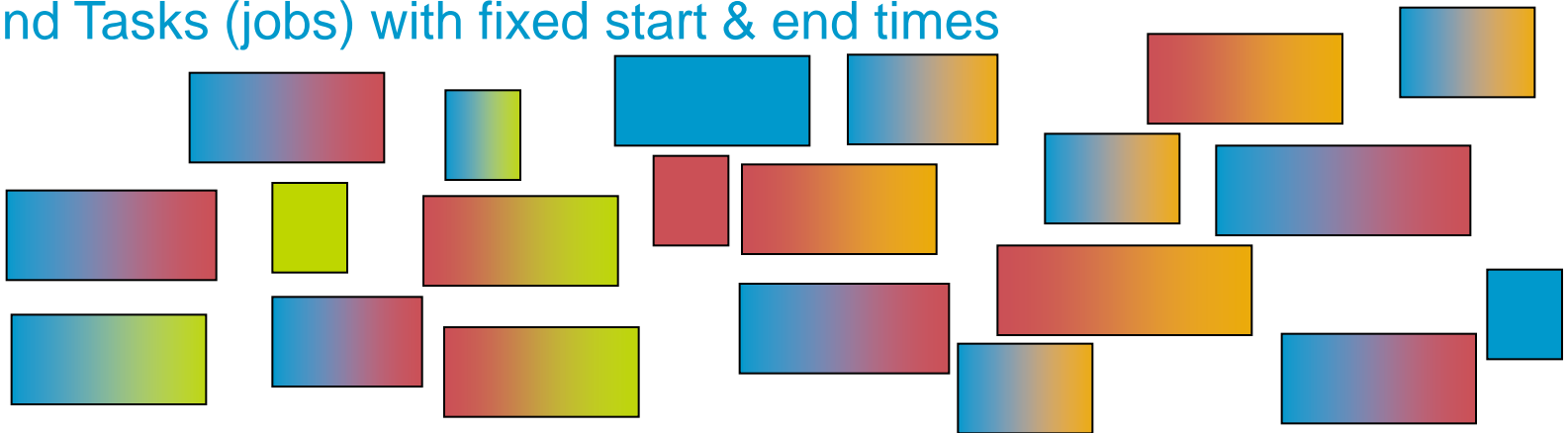
$$\sigma(t) \sim \sigma_L(t) = \sum_{l=1}^L k_l \int_0^t K_{\tau_l, \beta_l}(t-\tau) \dot{j}(\tau) d\tau$$

# Personnel Task Scheduling Problems

Given a set of shifts/workers:



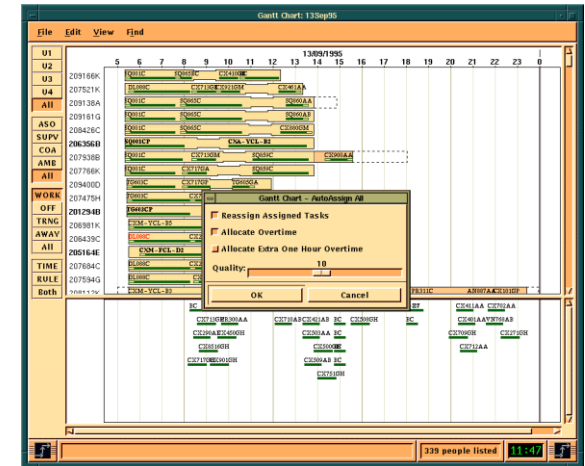
and Tasks (jobs) with fixed start & end times



Assign all tasks to people that are qualified for it (max tasks assigned, minimum shifts used)

# Scheduling of tasks for airport ground staff

- Ground staff at an airport
- Various tasks relating to servicing aircraft and passengers
- Task times driven by airline schedules
- Different qualifications for task by staff.
- Want to assign all tasks to staff each day, minimising casual staff/overtime required or tasks that are under-staffed.





# Hunter Valley Rail Scheduling

- Create schedules for trains between coal-mines in the Hunter Valley & terminals in Newcastle
- Possible roundtrips with fixed start-end times created by train “paths”
  - path = time slot on train line
- In addition to train “workers”
  - Loadpoints at the mines
  - Tracks where trains can wait
  - Dump stations
  - Terminal resources (eg stackers)
- Want to assign as many roundtrips as possible to the trains
  - subject to a range of additional side constraints
  - multiple types of soft constraints (preferences for a “good” schedule)



$$(-1)^m \frac{d^m}{dt^m} \geq 0, \quad m=1, 2, \dots$$

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# Exact Methods



# Integer Linear Programming Formulation

$$\min \sum_{w \in W} y_w + \sum_{j \in J} M u_j$$

$$\sum_{w \in P_j} x_{jw} + u_j = 1 \quad \forall j \in J$$

Set of cliques  
of overlapping  
tasks for shift  $w$

$$\sum_{j \in K} x_{jw} \leq y_w \quad \forall w \in W, K \in C^w$$

Task  $j$  assigned shift  $w$   $x_{jw} \in \{0, 1\} \quad \forall w \in W, j \in T_w$

Shift  $w$  used  $0 \leq y_w \leq 1 \quad \forall w \in W$

Task  $j$  unallocated  $0 \leq u_j \leq 1 \quad \forall j \in J$

# Triplet based branching

Job 1 – x value 0.4



Job 1 – x value 0.3



Job 2 – x value 0.6

Conflicting triplet:

3 jobs with one overlapping two otherwise compatible jobs

- Branch by selecting largest fractional variable in a conflicting triplet
- Any LP solution without conflicting triplets is integer (or can be turned into an equivalent integer solution)

# Packing problem

- Find the maximum value set of tasks that can be completed by one (given) worker  $w$

$$\begin{aligned} \max \quad & \sum_{j \in T_w} \pi_j x_j \\ \text{s.t.} \quad & \sum_{j \in K} x_j \leq 1 & \forall K \in C^w \\ & x_j \in \{0, 1\} & \forall j \in T_w \end{aligned}$$

- Can be solved in  $O(n)$  where  $n$  is number of tasks that  $w$  is qualified to carry out
- Simple shortest-path/dynamic programming algorithm

# Preference Adjustment Heuristic

Start with preferences  $\pi_{jw} = x_{jw}$  (fractional LP solution)

**While** not done:

Solve packing problems for all shifts  $w$

**If** all jobs allocated, choose a shift to remove

**Otherwise** choose an unallocated task  $k$

For each  $w$ , calculate the minimum change in  $\pi_{kw}$  that would result in  $j$  being allocated to  $w$  (from reduced costs)

Choose a  $\underline{w}$  for which this change is smallest

Increase  $\pi_{k\underline{w}}$  and decrease  $\pi_{j\underline{w}}$  for all other tasks  $j$

# Column Generation

Price variables by solving packing problem using duals as preferences

1. Original Formulation: Add the  $x_{jw}$  that are used in the packing
2. Compact Formulation: Use binaries  $z_{wP}$  to select pattern  $P$  for shift  $w$

$$\begin{aligned} \min \quad & \sum_{w \in W} \sum_{P \in \mathcal{P}^w} z_{wP} + \sum_{j \in J} M u_j \\ \text{s.t.} \quad & \sum_{w \in W} \sum_{\substack{P \in \mathcal{P}^w: \\ j \in P}} z_{wP} + u_j = \underline{1} \quad \forall j \in J \\ & \sum_{k \in \mathcal{P}^w} z_{wk} \leq 1 \quad \forall w \in W \\ & z_{wP} \in \{0, 1\} \quad \forall w \in W, P \in \mathcal{P}^w \\ & 0 \leq u_j \leq 1 \quad \forall j \in J \end{aligned}$$

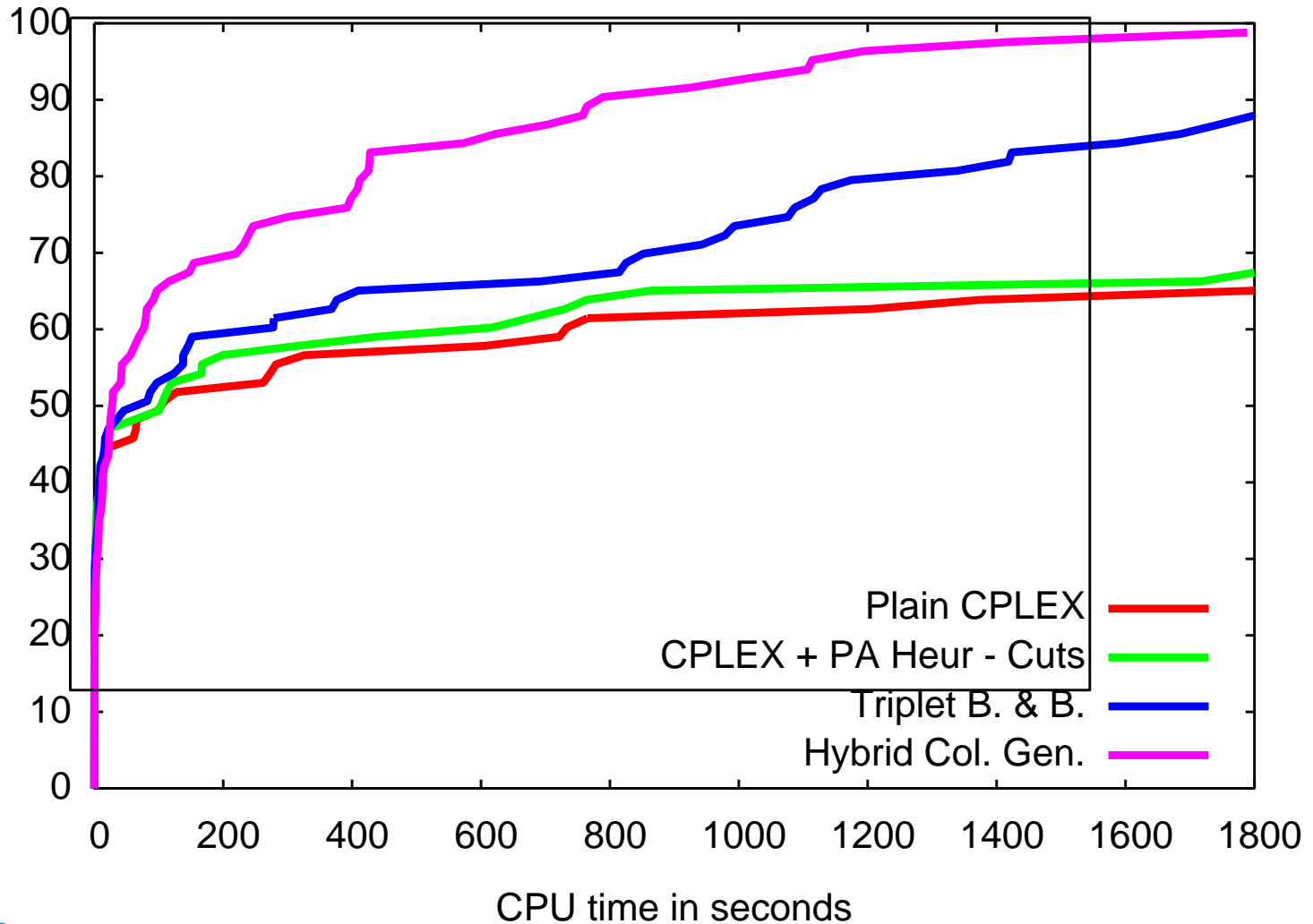
3. Hybrid: use Compact Formulation at root node and original formulation during B&B

Since (2) is faster but (1) has generally less fractional solutions

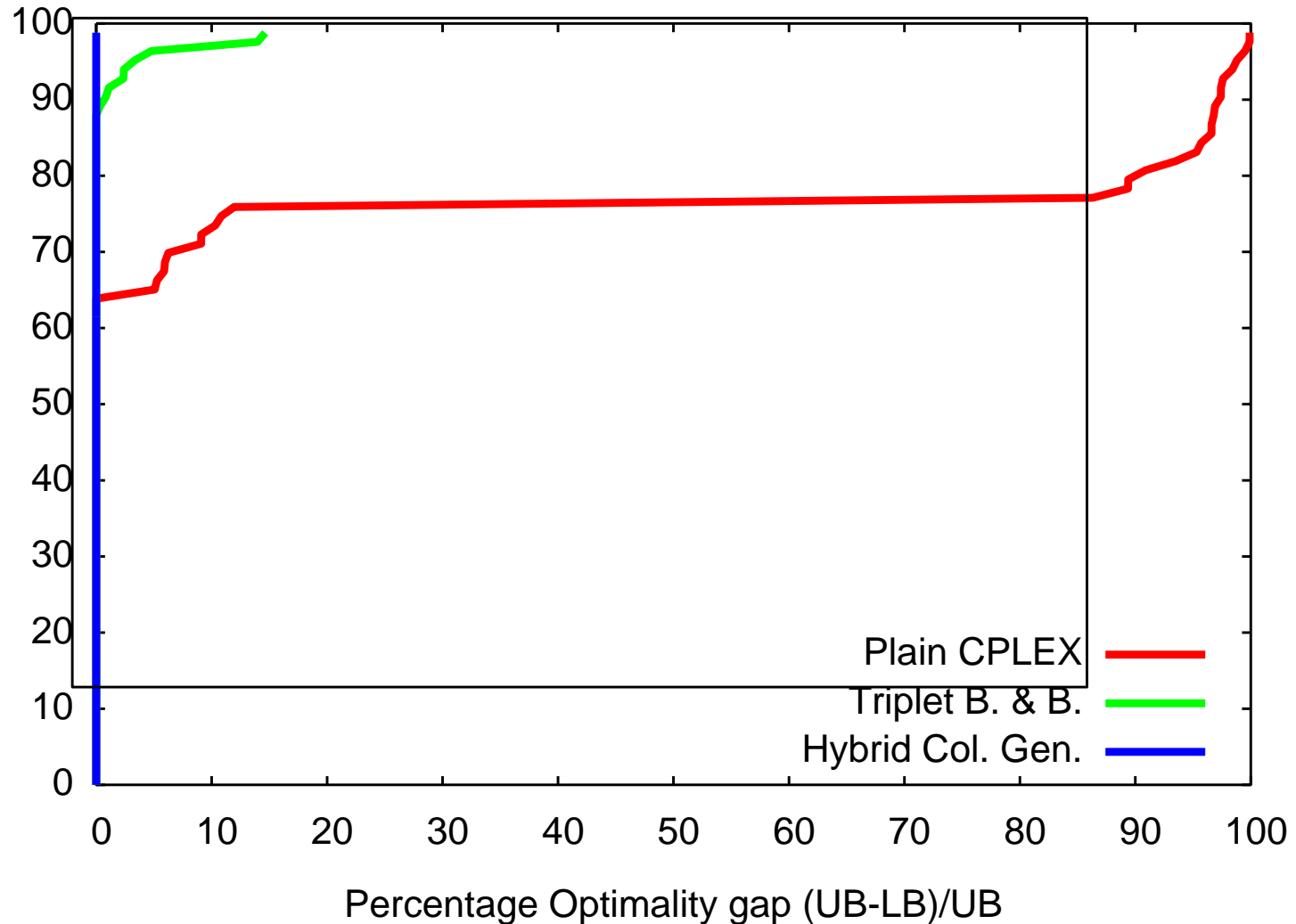
# Computational Results

- Randomly generated instances
- About 80 instances with up to 380 shifts and 900 jobs used for exact method results
  - An additional 50 instances with up to 420 shifts and 2100 jobs used for the heuristic results
- Run on 4 \* Quad-core Intel Xeon processors @ 2.93 GHz with 64Gb RAM

# Problems solved within 1800 CPU seconds



# Optimality Gaps



- All problems solved with column generation method



$$(-1)^m \frac{d^m}{dt^m} \geq 0, \quad m=1, 2, \dots$$

$$K_{\tau_l, \beta_l}(t) = \exp(- (t/\tau_l)^{\beta_l})$$

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# Lagrangian Heuristics

# Lagrangian Approach

$$\min \sum_{w \in W} y_w + \sum_{j \in J} M u_j$$

$$\sum_{w \in P_j} x_{jw} + u_j \geq 1$$

Relax with dual variables  $\pi_j$

$$\sum_{j \in K} x_{jw} \leq y_w \quad \forall w \in W, K \in C^w$$

$$x_{jw} \in \{0, 1\} \quad \forall w \in W, j \in T_w$$

$$0 \leq y_w \leq 1 \quad \forall w \in W$$

$$0 \leq u_j \leq 1 \quad \forall j \in J$$

# Lagrangian Method

- **Basic approach:**
  - Start with some dual value, solve relaxed problem, update dual vector, iterate
- **Pros:**
  - Fast
  - Reasonable lower bounds
- **Cons:**
  - Tends to zig-zag
  - No guarantee of primal feasible solutions
  - The solution for the relaxed problem may not be primal feasible for any value of the dual vector

# Volume Algorithm

- Choose an initial**  $\pi_0 \in \mathbb{R}^m$  **compute**  $x_0 \in \text{Argmin } L(x, \pi_0)$   
**Let**  $v_0 := Ax_0 - b$  **Violation**

$z_1 = x_0$       **estimate of primal solution**       **$t = \text{minor iter.}$**   
 $w_1 := v_0$ ,      **search direction**       **$k = \text{major iter.}$**   
 $\hat{\pi}_1 = \pi_0$       **stability center (current best dual)**       **$t = k = 1$**
- Given**  $\hat{\pi}_k$  **& step length**  $s_t > 0$  **Let**  $\pi_t = \hat{\pi}_k + s_t w_t$
- Solve Lagrangean subproblem**

$x_t \in \text{Argmin } L(x, \pi_t)$        $v_t := Ax_t - b$
- If**  $\theta(\pi_t) > \theta(\hat{\pi}_k)$  **AND**  $\langle w_t, v_t \rangle > 0$  **then**  
     **do a serious step, update stability center**  $\hat{\pi}_{k+1} = \pi_t$   
      $k++, t_k := t$       **referred to as a green iteration**

**else: null step, do nothing (aka yellow or red iteration)**
- Compute step size**  $s_{t+1}$  **and for some**  $0 \leq \alpha_t \leq 1$

$z_{t+1} := \alpha_t x_t + (1 - \alpha_t) z_t$

$w_{t+1} := \alpha_t v_t + (1 - \alpha_t) w_t$        $s_t = \mu \frac{\text{UB} - \theta(\pi_t)}{\|w_t\|^2}$
- Set**  $t++$ , **go to step 1**

# Volume Algorithm

- “Standard” Lagrangian relaxation approach
- Approximates primal solution
- Stabilises search direction by updating using a combination of previous search direction and current sub-gradient

$$\begin{aligned} z_{t+1} &:= \alpha_t x_t + (1 - \alpha_t) z_t \\ w_{t+1} &:= \alpha_t v_t + (1 - \alpha_t) w_t \end{aligned} \quad s_t = \mu \frac{\text{UB} - \theta(\pi_t)}{\|w_t\|^2}$$

# Wedelin's Lagrangian Method

- Heuristic that tries to achieve primal feasibility by “splitting” Lagrangian multipliers  $\pi_j$  into  $\pi_{jw}$  (ie different for each shift  $w$ ) and adding a perturbation
- Performs co-ordinate ascent to find good Lagrangian multiplier values. Given an unassigned task  $j$

$$\pi_{j\bar{w}} = \frac{r^- + r^+}{2} + \delta$$

$$\pi_{jw} = \max\left\{\frac{r^- + r^+}{2} - \delta, 0\right\} \quad \forall w \in P_j, w \neq \bar{w}$$

- Here
  - $\delta$  is a “small” perturbation
  - $r^-$  &  $r^+$  are the smallest & second smallest reduced cost for the task to any shift
  - Should make reduced cost negative for  $x_{jw}$  but positive for all others

# Combined Algorithm

- Start with Volume Algorithms
  - Gives strong lower bound and starting point for Wedelin
- Use Wedelin's method to generate a good upper bound
  - Fairly similar to preference adjustment heuristic used for the exact methods
- This works quite well but ...

... what are the other 15 CPU cores going to do?

Can solve Lagrangian sub-problems in parallel but unless dealing with significantly larger problem instances than considered here these are too small to give good parallelisation

→ Hybridisation with Particle Swarm Optimisation

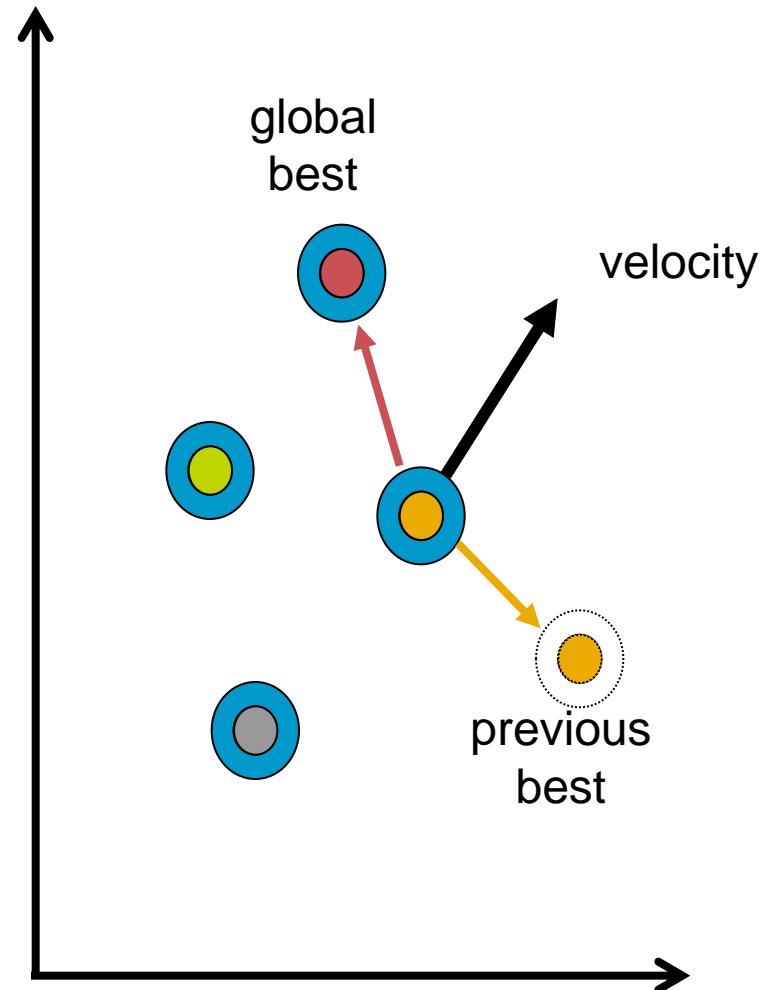
# Particle Swarm Optimisation

- Solution represented by
  - Continuous vector of variable values (**position**)
  - Search direction vector (**velocity**)
- Update velocity
  - Velocity as weighted sum of
    1. previous velocity,
    2. direction to best solution found so far (*global optimisation*),
    3. direction to particle's best solution. (*local optimisation*)

Update position based on velocity

$$\vec{v} \leftarrow \omega \vec{v} + \phi_p r_p (\vec{p} - \vec{x}) + \phi_g r_g (\vec{g} - \vec{x})$$

$$\vec{x} \leftarrow \vec{x} + \vec{v}$$





# Hybrid Lagrangian Particle Swarm Opt.

- 2 Position vectors:
  - Lagrangian and perturbation (number of constraints/variables)
- 2 velocity vectors
- Follow basic pattern of PSO but
  - Replace update of Lagrangian velocity towards particle's best with update in direction of subgradient
  - Use Wedelin's method for determining local update direction of the perturbation velocity.
    - Add small constant for the "preferred" shift assignment of a job and subtract it for all others
- Note:
  - Added a repair heuristic to run occasionally
  - Can still obtain lower bounds (albeit weaker ones) even when there is a non-zero perturbation of the Lagrangian vector/matrix

# Hybrid Lagrangian Particle Swarm Opt.

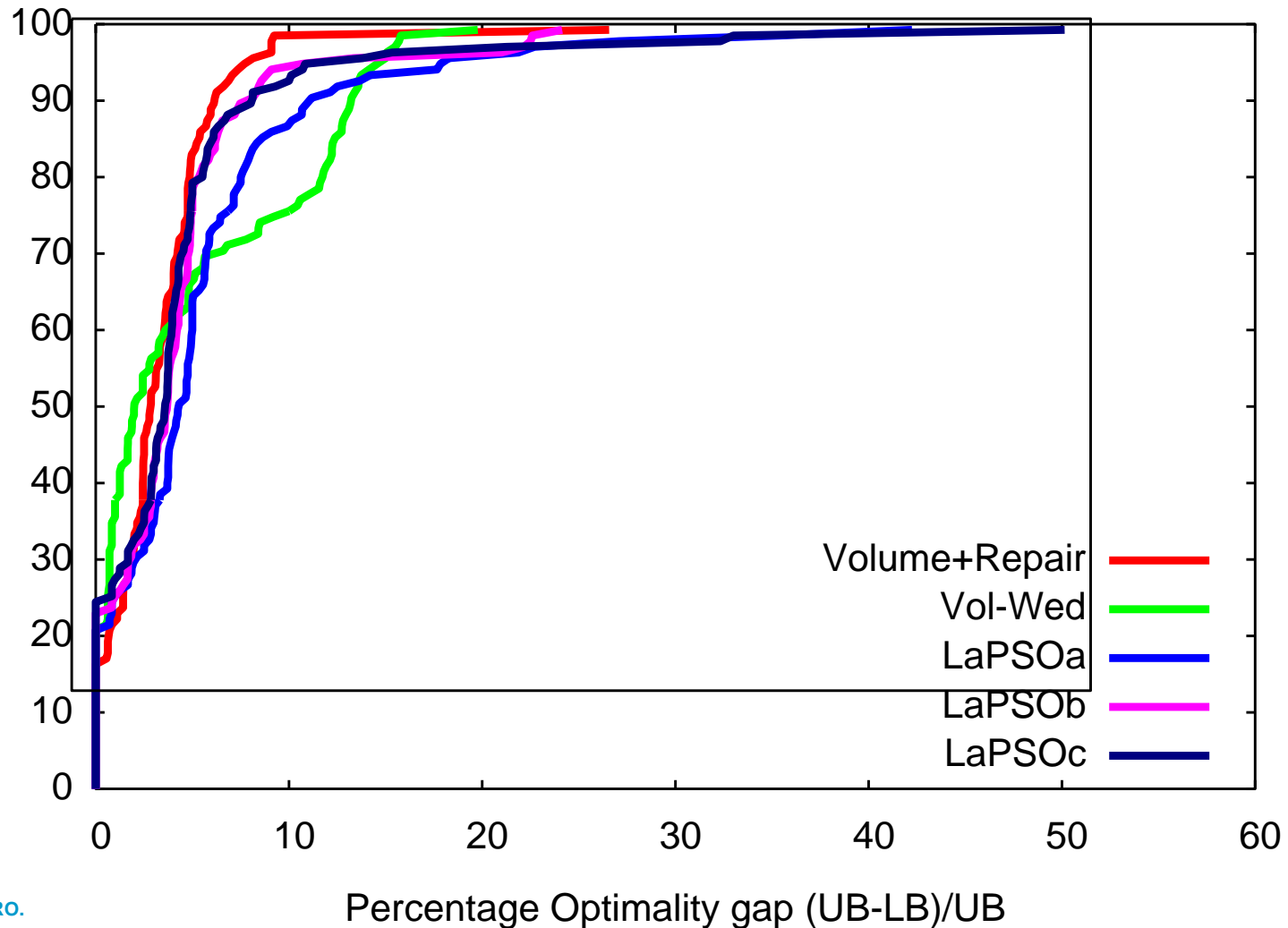
- 2 Position vectors:
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- Follow basic pattern of PSO but
  - Replace update of Lagrangian velocity towards particle's best with update in direction of subgradient
  - Use Wedelin's method for determining local update direction of the perturbation velocity.
    - Add small constant for the "preferred" shift assignment of a job and subtract it for all others
- One particle per CPU core, running in parallel with synchronisation after each iteration to update the global best
- Note:
  - Added a repair heuristic to run occasionally
  - Can still obtain lower bounds (albeit weaker ones) even when there is a non-zero perturbation of the Lagrangian vector/matrix

# Methods compared

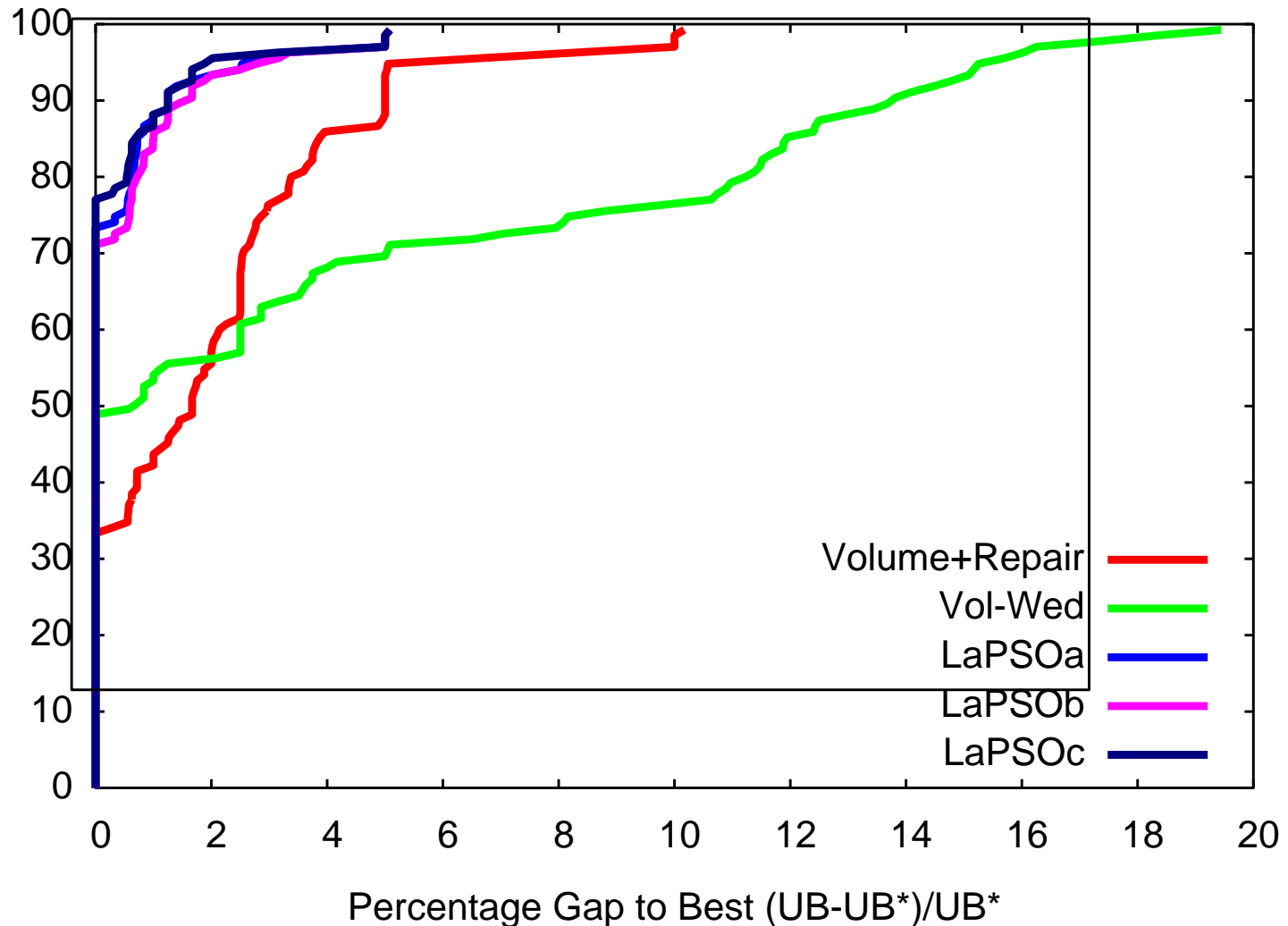
- **Volume+Repair**
  - Run volume algorithm only (no Wedelin)
  - Use a repair heuristic every few iterations
  - Lagrangian sub-problems solved in parallel
- **Vol-Wed**
  - First volume algorithm then Wedelin's method
  - No parallelisation
- **LaPSOa – LaPSOc**
  - Three runs of the Lagrangian Particle Swarm Opt. heuristic
  - First run has slightly different parameter settings to the other two
  - Shows sensitivity to randomisation & parameter settings
  - Uses 16 particles for 16 cores

# Optimality gap of heuristics

Compare: worst gap for B&B ~15%, Volume+Repair ~ 10%, Vol-Wed ~ 20% but exact methods perform very poorly on larger problems even with 5000 CPU sec

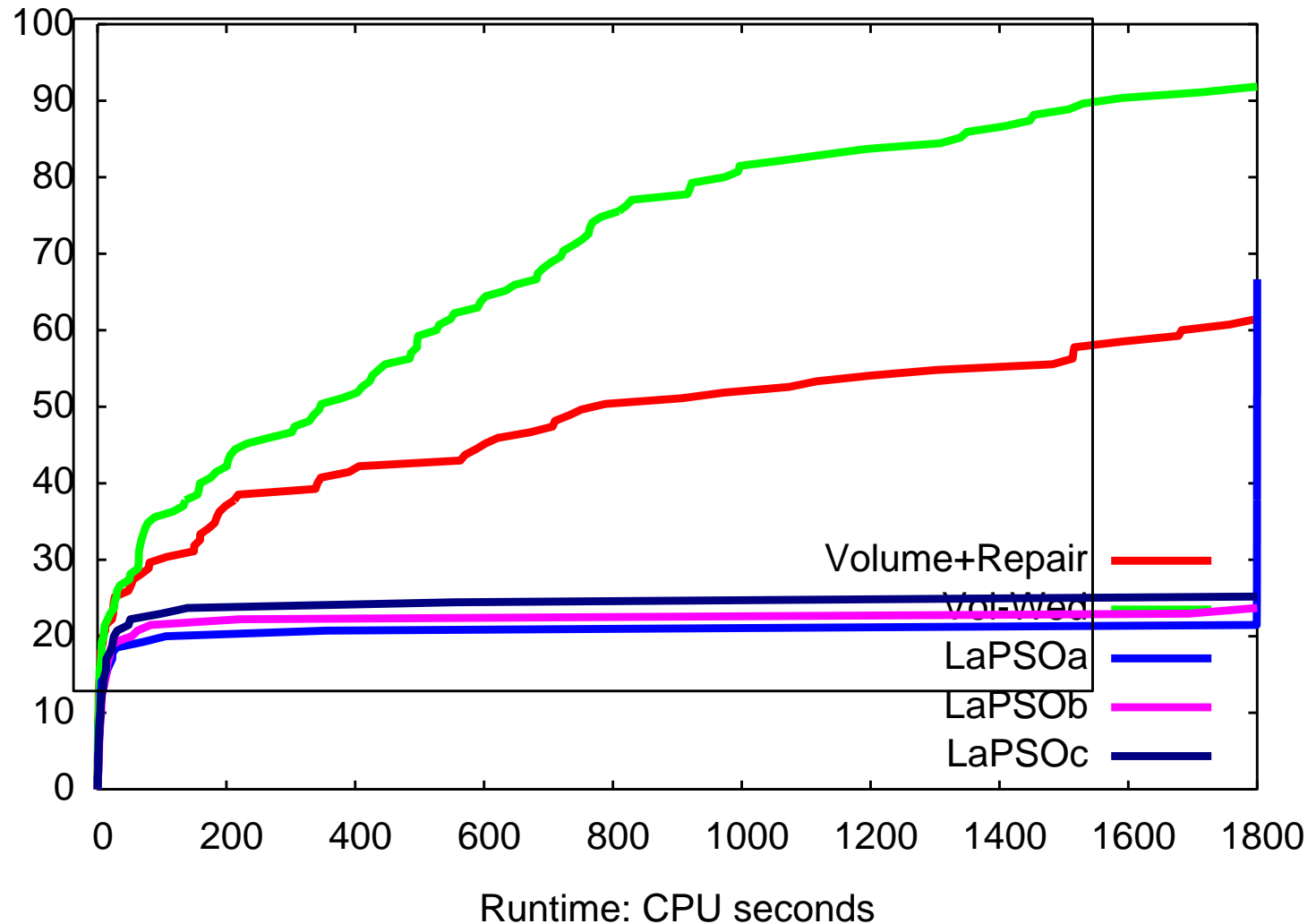


# Gap to best solution found by any method



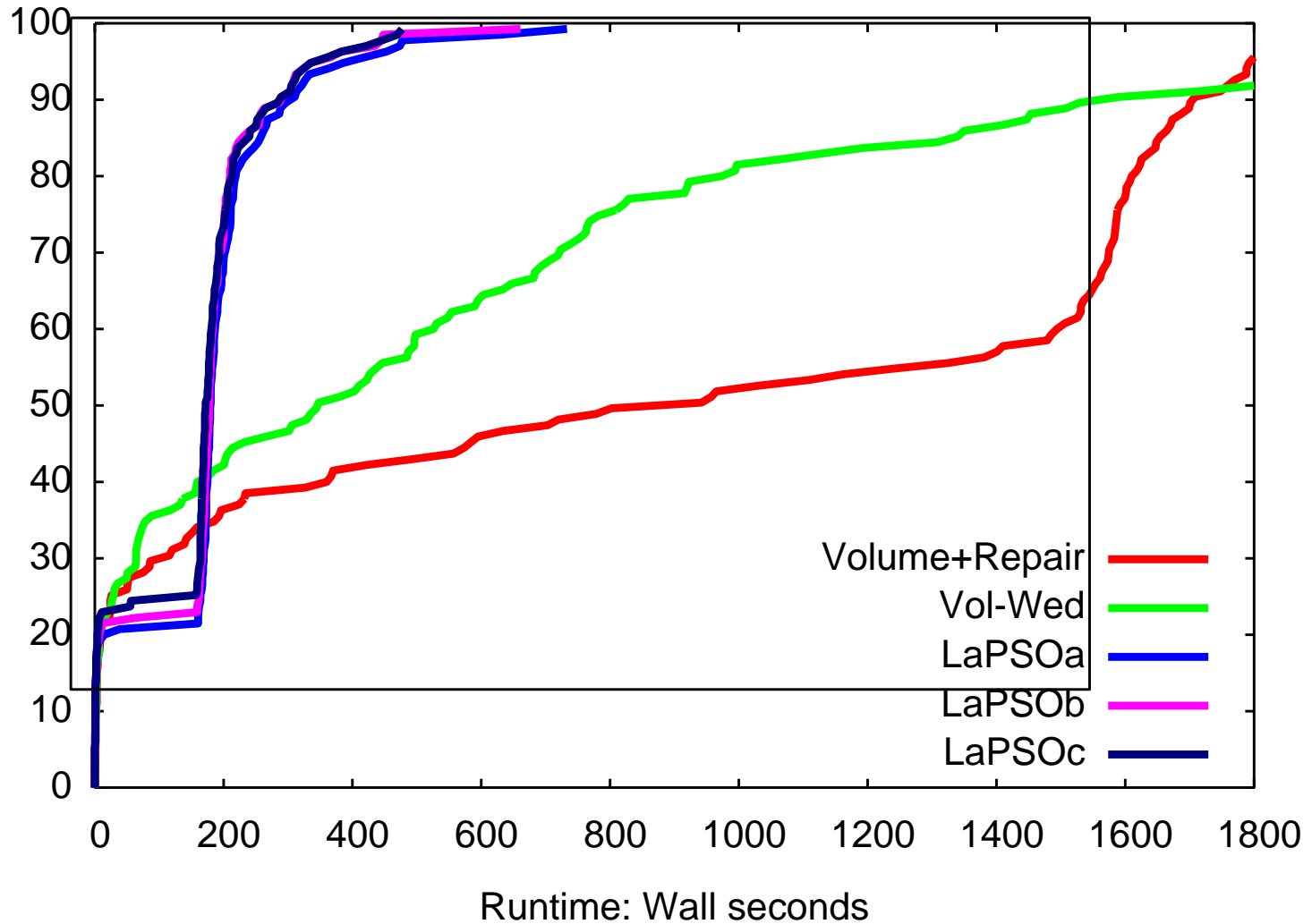
→ Main advantage of Volume-Wedelin method is in lower bounds

# CPU time required

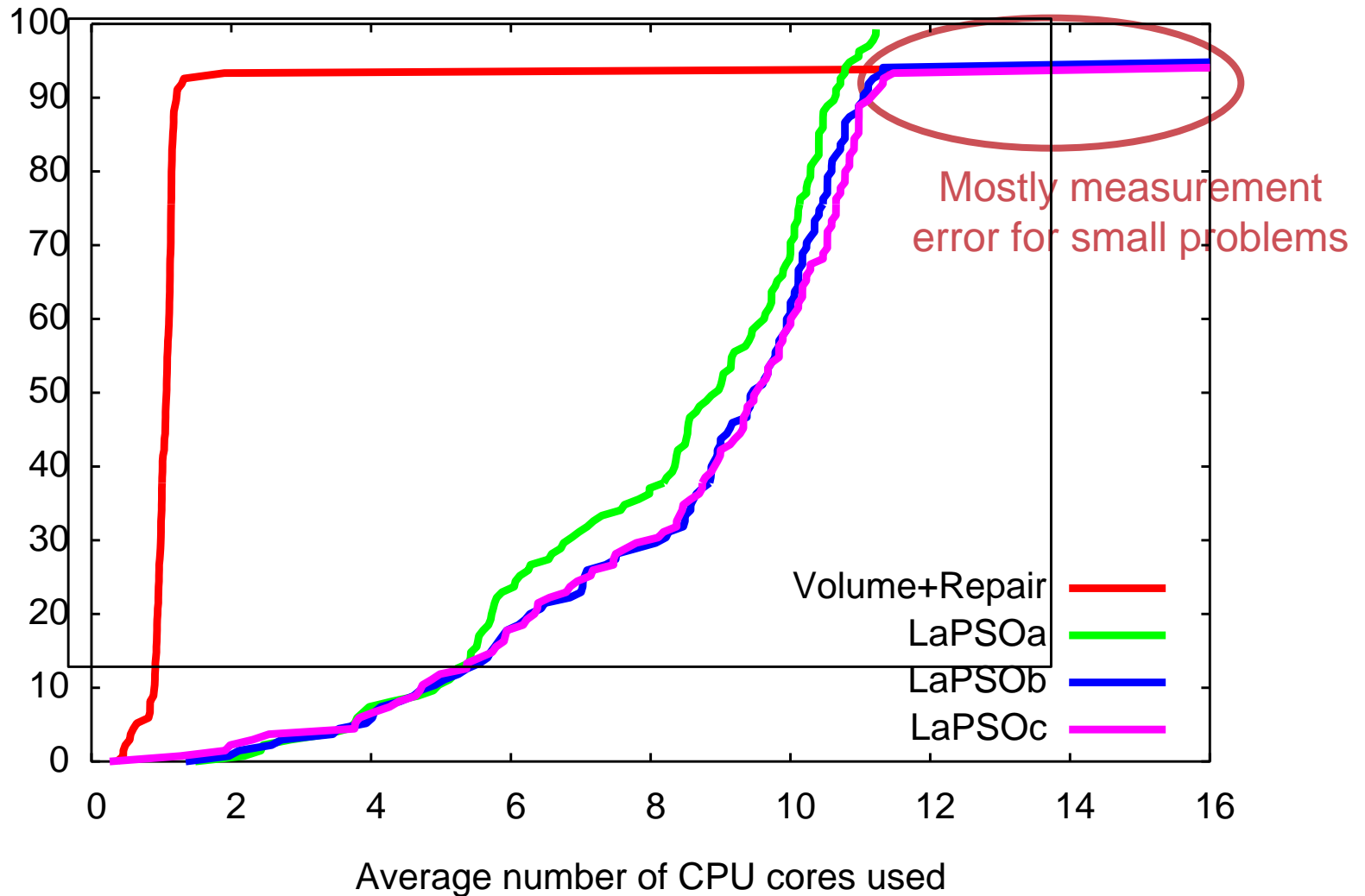


→ Particle Swarm Method doesn't know when to give up!

# Elapsed (wall) time required



# Average number of CPU cores used





# Conclusions

- Some gains from column generation and custom branching scheme, root-node heuristic...
- but overall simplex based methods only effective if provable optimality is important and problems are small
- Lagrangian methods perform well
  - Need to exploit strengths of both Volume method and Wedelin's heuristic approach to get good solution
- Particle swarm optimisation provides good framework for parallelisation

## Questions:

- How to increase CPU utilisation on a parallel machine
- What should I do with the 32 cores of our newest machine given that I can't even use 16 effectively?

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# Thank you

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