MUNI
FACULTY
OF INFORMATICS

Elegance of Simplicity: Designing Metaheuristics for Real-World Applications

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Application domains

1. Course Timetabling
2. Vehicle Routing
3. Cross-Domain Search
4. Warehouse Planning

Course Timetabling

University course timetabling

- Curriculum-based timetabling
  - curriculum: set of courses
  - each student is enrolled in (one or more) curricula
  - goal: timetabling all courses in a curriculum without overlapping
  - also typical for timetabling in high schools
- Enrollment-based timetabling
  - each student is individually pre-enrolled/enrolled in a set of courses
  - student conflict:
    student is unable to take (two) enrolled courses due to overlap
  - goal: finding a timetable minimizing the number of student conflicts

University course timetabling in UniTime

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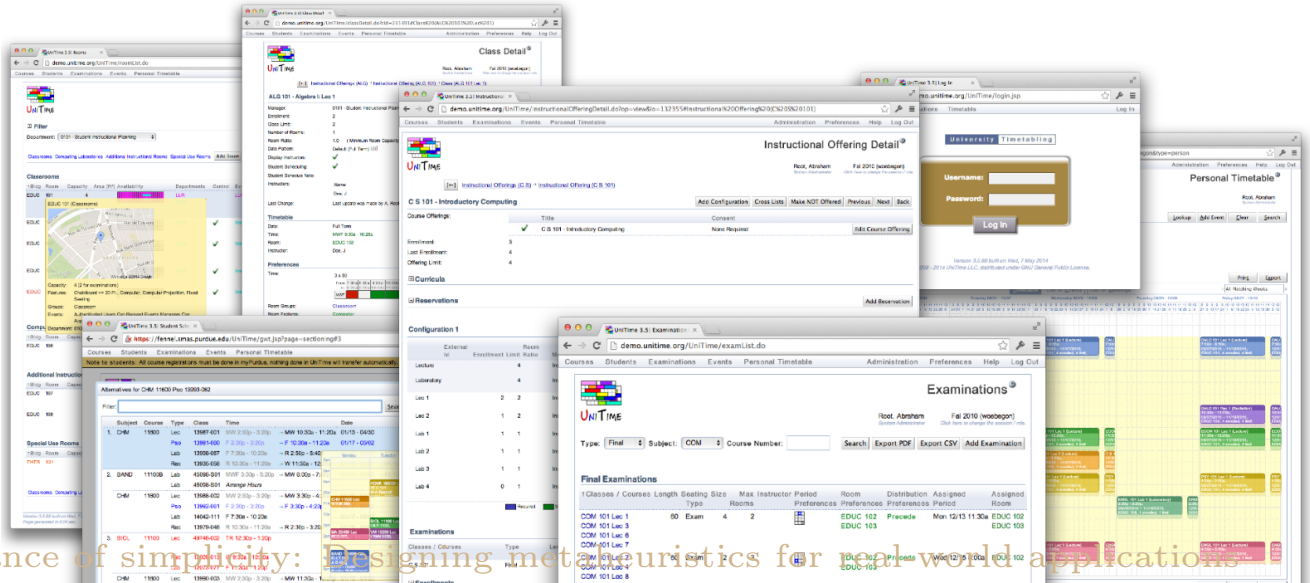

Developed at Purdue University (USA) in collaboration with FI MU and MFF UK

Comprehensive system for university timetabling

- timetabling of courses with curricula and enrollments
- timetabling for students, exams, teachers
- open source, web-based, in Java
- developed since 2001
- in apereo foundation from 2015
  - for open-source projects in higher education

Applications worldwide

- voluntary registrations: over 600 from 113 countries
- in production: over 100 institutions from 58 countries

Model in UniTime

Optimization problem with hard and soft constraints

- domain for each variable
  - course timetabling: encodes combination of eligible times & classrooms
- hard constraints: must be satisfied, e.g.,
  - time & classroom requirements
  - course structure
  - non-overlapping for classrooms, teachers, and other resources
- soft constraints: represent objective functions,
  whose weighted sum is minimized, e.g.,
  - the number of student conflicts
  - preferences on time & classroom

Iterative forward search: Algorithm

Constructive non-systematic algorithm

- works with partial solutions
  - empty $\longrightarrow$ partial $\longrightarrow$ complete solution
- works with feasible/consistent solutions
  - hard constraints must be satisfied in any partial solution

Iterative forward search: Algorithm

Constructive non-systematic algorithm

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Basic idea: mimics manual timetable construction

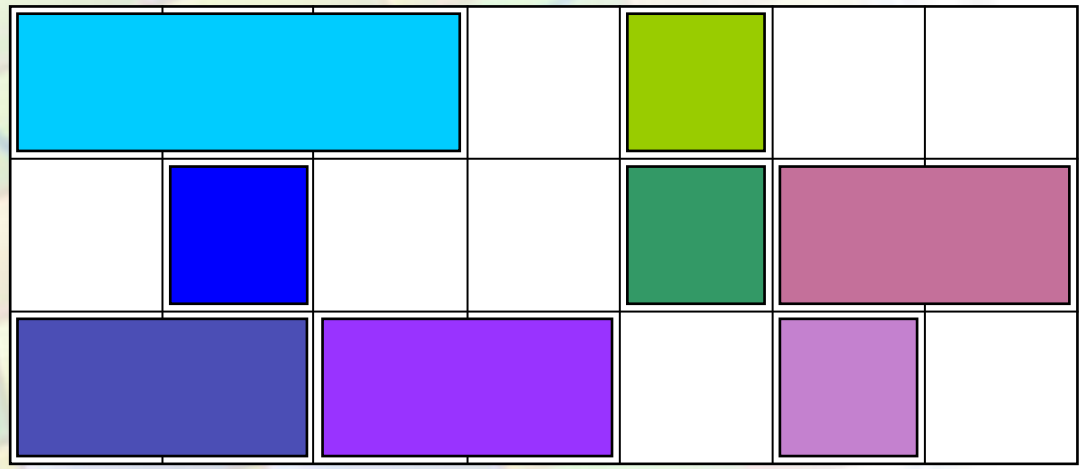
- starts with an empty solution
- selects a new variable to assign
- if it finds a conflict,
  unassigns all variables conflicting with the selected variable

Conflict-based statistics

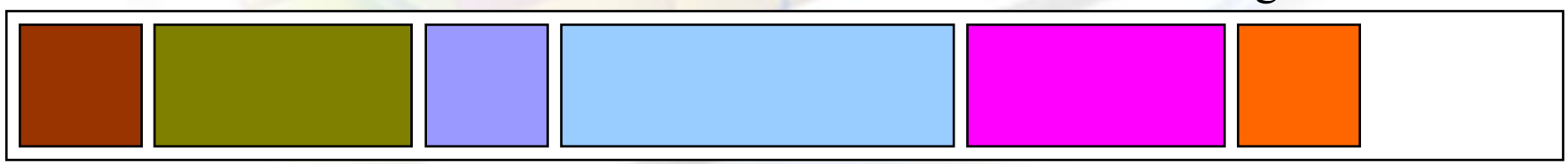
- simple learning process to avoid cycling

Iterative Forward Search Algorithm

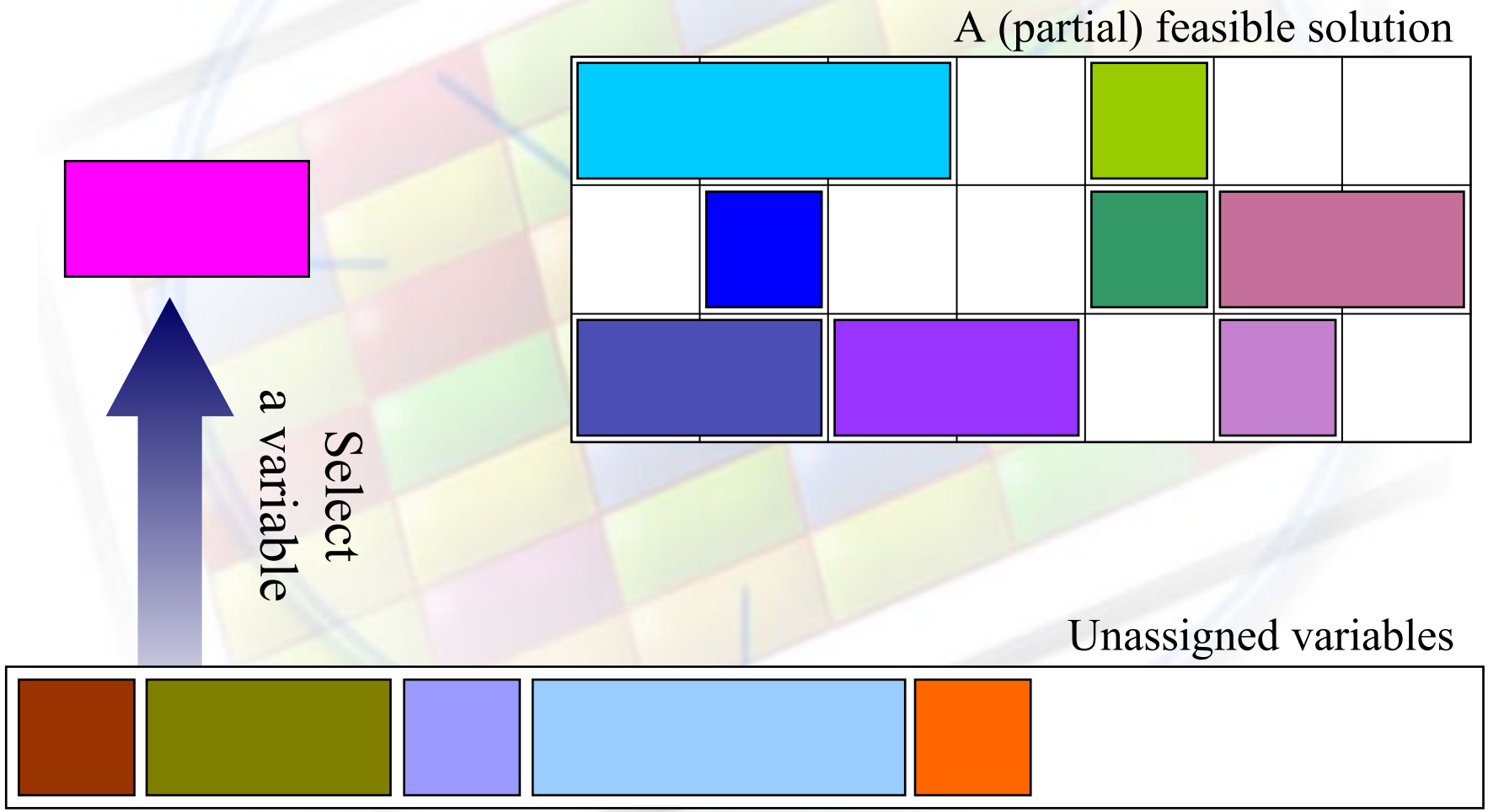
A (partial) feasible solution



Unassigned variables



Iterative Forward Search Algorithm



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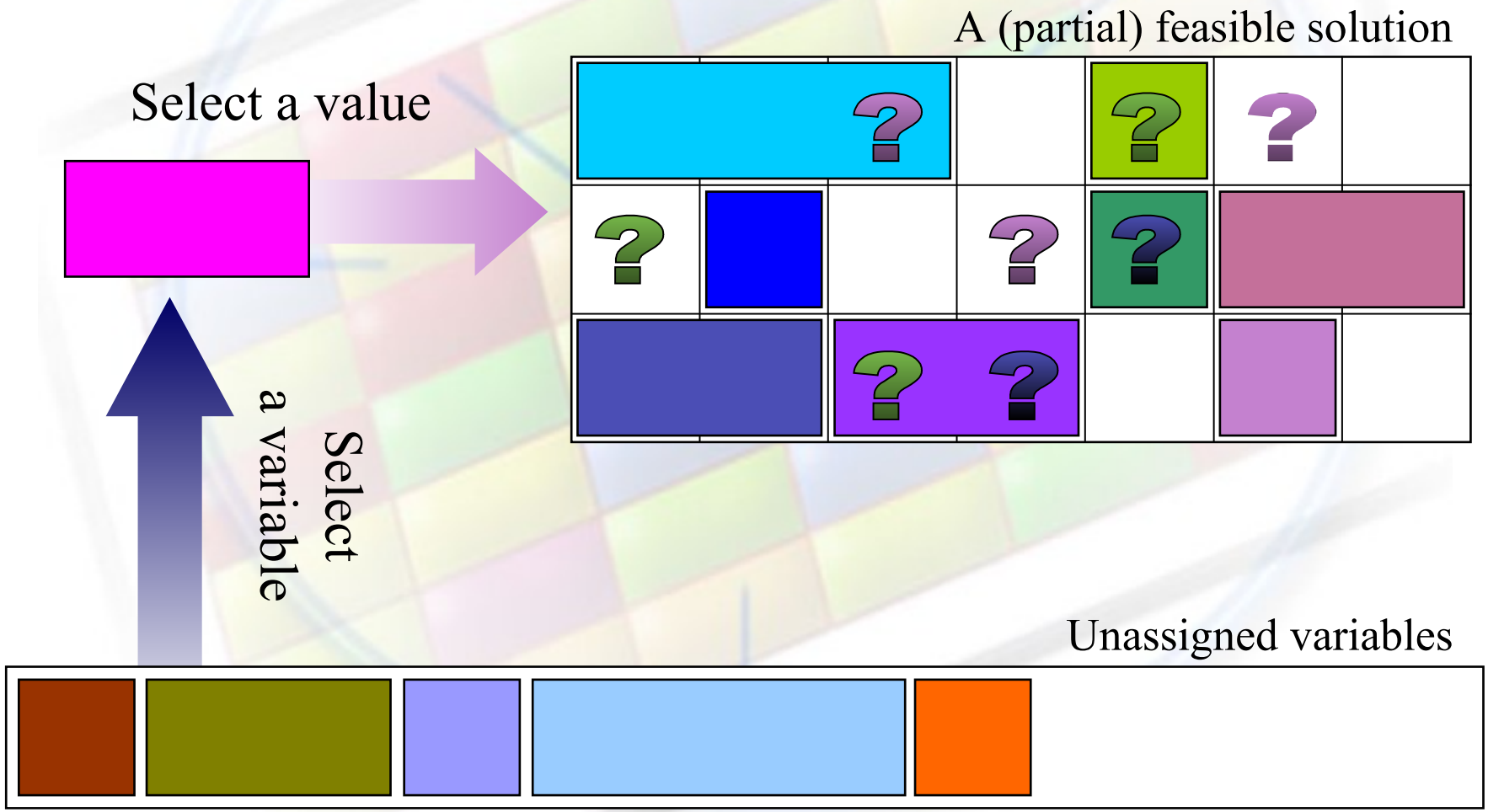

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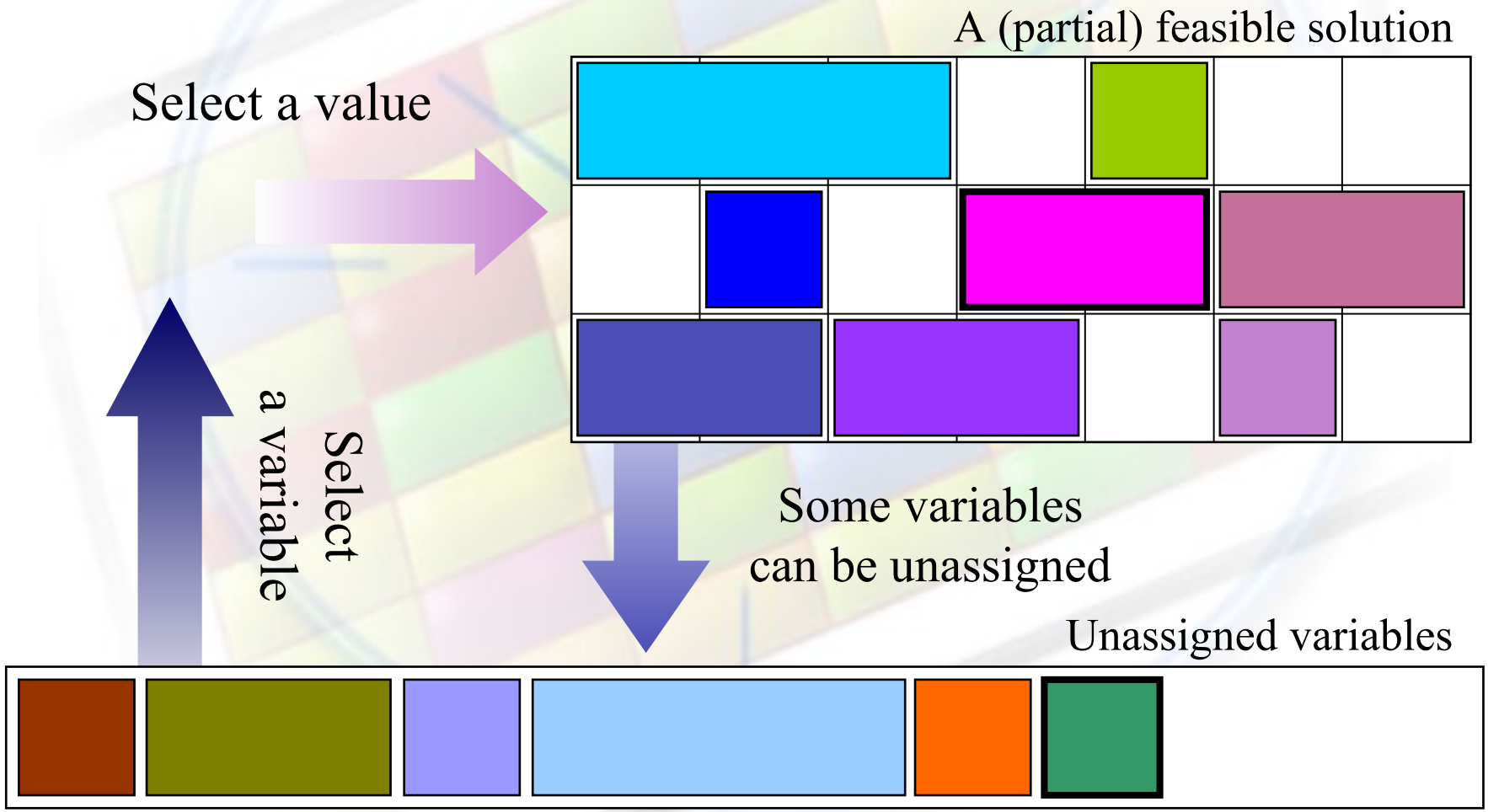

Conflict-based statistics (CBS): Example

Crucial: how to select value for each variable?

A partial timetable

Room/Time	8:00	9:00	10:00
100	Geography (G) *James*	Biology (B) *Peter*	
200	Physics (P) *Thomas*	English (E) *David*	Chemistry (Ch) *John*

Requirements for Math (M) with assigned instructor *Peter*

- must be in the classroom 200
- must be scheduled at 8:00 or 9:00

Conflict-based statistics (CBS): Simple learning

Room/Time	8:00	9:00	10:00
100	Geography (G) *James*	Biology (B) *Peter*	
200	Physics (P) *Thomas*	English (E) *David*	Chemistry (Ch) *John*

Data stored in CBS

The CBS remembers how many times an assignment caused another variable to be unassigned in past iterations

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- Placing Math at 08:00 caused Physics to be unassigned from 200 5 times in the past: $M_{200,8:00} \Rightarrow 5 \times \neg P_{200,8:00}$

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- Placing Math at 09:00 caused English to be unassigned from 200 4 times in the past: $M_{200,9:00} \Rightarrow 4 \times \neg E_{200,9:00}$

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Room/Time	8:00	9:00	10:00
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  Placing Math at 09:00 caused Biology to be unassigned from 100 2 times in the past: $M_{200,9:00} \Rightarrow 2 \times \neg B_{100,9:00}$

Value selection using CBS

Value selection heuristic:

- select the value with the lowest number of conflicts weighted by their past frequency

Options:

- Math at 8:00: $M_{200,8:00} \Rightarrow 5 \times \neg P_{200,8:00}$
  $\Rightarrow$ P is unassigned, CBS: 5

Value selection using CBS

Value selection heuristic:

- select the value with the lowest number of conflicts weighted by their past frequency

Options:

- Math at 8:00: $M_{200,8:00} \Rightarrow 5 \times \neg P_{200,8:00}$
  $\Rightarrow$ P is unassigned, CBS: 5
- Math at 9:00: $M_{200,9:00} \Rightarrow 4 \times \neg E_{200,9:00}$
  $M_{200,9:00} \Rightarrow 2 \times \neg B_{100,9:00}$
  (B and M taught by *Peter*, i.e., $B_{100,9:00}$ conflicts with $M_{200,9:00}$)
  $\Rightarrow$ both E and B are unassigned, CBS: $4 + 2$

Value selection using CBS

Value selection heuristic:

- select the value with the lowest number of conflicts weighted by their past frequency

Options:

- Math at 8:00: $M_{200,8:00} \Rightarrow 5 \times \neg P_{200,8:00}$
  $\Rightarrow$ P is unassigned, CBS: 5
- Math at 9:00: $M_{200,9:00} \Rightarrow 4 \times \neg E_{200,9:00}$
  $M_{200,9:00} \Rightarrow 2 \times \neg B_{100,9:00}$
  (B and M taught by *Peter*, i.e., $B_{100,9:00}$ conflicts with $M_{200,9:00}$)
  $\Rightarrow$ both E and B are unassigned, CBS: $4 + 2$

Using CBS:

- IFS chooses 8:00 for Math because $5 < 4 + 2$.
- Math is assigned to 8:00
- Physics is unassigned and will be resolved in the next iteration

Value selection using CBS

Value selection heuristic:

- select the value with the lowest number of conflicts weighted by their past frequency

Options:

- Math at 8:00: $M_{200,8:00} \Rightarrow 5 \times \neg P_{200,8:00}$
  $\Rightarrow$ P is unassigned, CBS: 5
- Math at 9:00: $M_{200,9:00} \Rightarrow 4 \times \neg E_{200,9:00}$
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  (B and M taught by *Peter*, i.e., $B_{100,9:00}$ conflicts with $M_{200,9:00}$)
  $\Rightarrow$ both E and B are unassigned, CBS: $4 + 2$

Using CBS:

- IFS chooses 8:00 for Math because $5 < 4 + 2$.
- Math is assigned to 8:00
- Physics is unassigned and will be resolved in the next iteration
- CBS counter $M_{200,8:00} \Rightarrow \neg P_{200,8:00}$ incremented from 5 to 6

When do we count a conflict from CBS?

We only count a conflict if it leads to the removal of the assignment

Math has assigned instructor *Peter* $\Rightarrow$ conflicts with Biology

Room/Time	8:00	9:00	10:00
100	Geography (G) *James*	Biology (B) *Peter*	
200	Physics (P) *Thomas*	English (E) *David*	Chemistry (Ch) *John*

CBS

- $M_{200,8:00} \Rightarrow 5 \times \neg P_{200,8:00} \Rightarrow P$ is unassigned $5 < 4 + 2$
- $M_{200,9:00} \Rightarrow 4 \times \neg E_{200,9:00}$

  $M_{200,9:00} \Rightarrow 2 \times \neg B_{100,9:00}$

When do we count a conflict from CBS?

We only count a conflict if it leads to the removal of the assignment

Math has assigned instructor *Peter* $\Rightarrow$ no conflict with Biology

Room/Time	8:00	9:00	10:00
100	Geography (G) *James*	Biology (B) *John*	
200	Physics (P) *Thomas*	English (E) *David*	Chemistry (Ch) *John*

CBS

- $M_{200,8:00} \Rightarrow 5 \times \neg P_{200,8:00}$
- $M_{200,9:00} \Rightarrow 4 \times \neg E_{200,9:00} \Rightarrow E$ is unassigned $4 < 5$

  $M_{200,9:00} \Rightarrow 2 \times \neg B_{100,9:00}$: not counted now

- IFS with CBS used for course timetabling in UniTime
  to construct a reasonable initial complete solution
  - no parameter tuning
- Initial solution then improved with
  great deluge or simulated annealing with reheating

⇒ Remarkably simple approach which works very well!

- Presentation: today 15:40
  T. Müller, Instructor Scheduling in UniTime
- Overview paper about course timetabling in UniTime
  H. Rudová, T. Müller, K. Murray, Complex university course timetabling. *Journal of Scheduling*, 14(2): 187–207, 2011

International Timetabling Competition 2019

- 10 institutions from 5 continents
  have provided data
  for the ITC 2019 competition

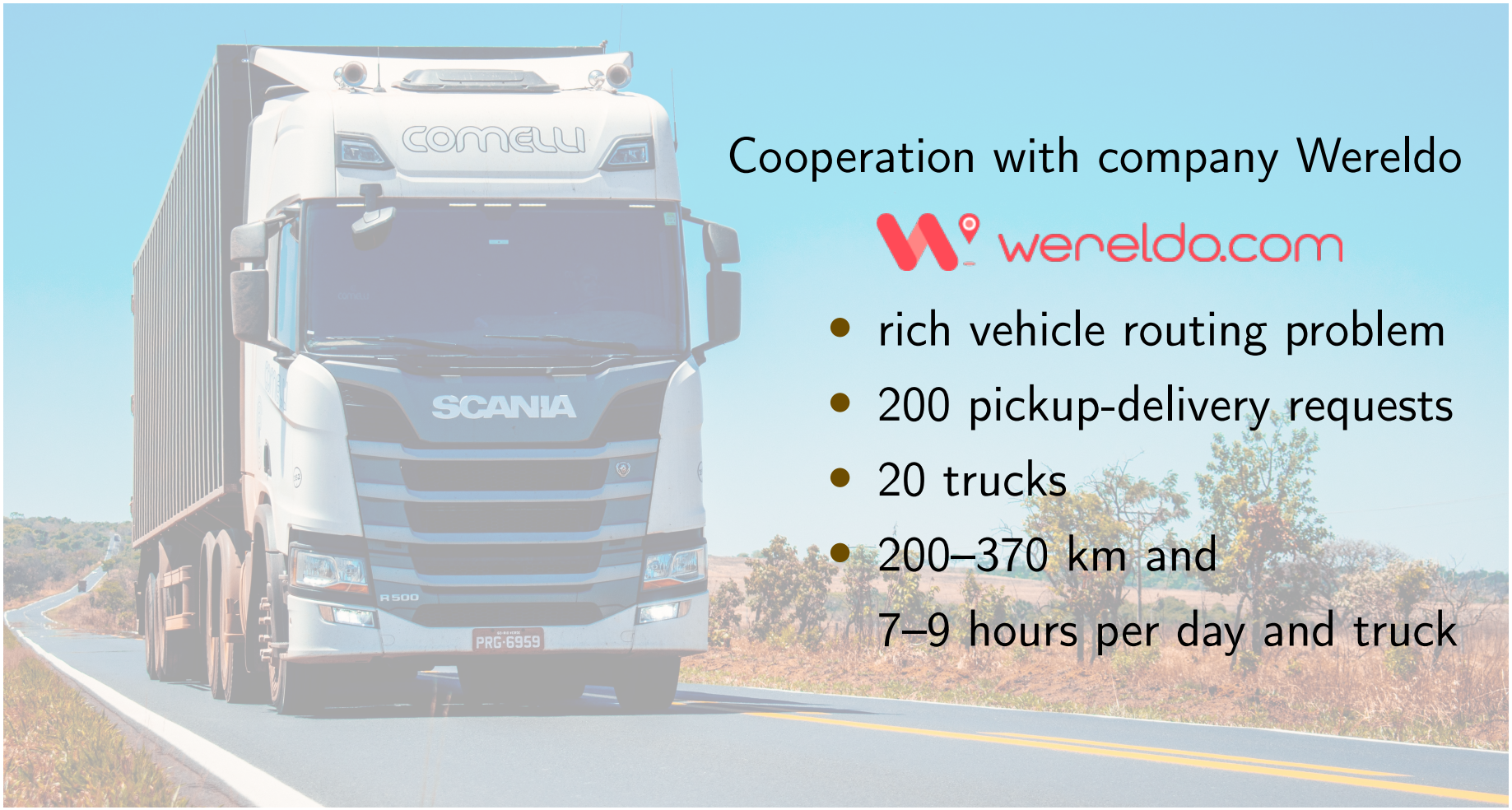
ITC 2019

- 30+5 real-world data instances available using UniTime
  - different size, different characteristics
  - XML format
  - solution validator
- Enrollment-based timetabling
  minimize the weighted sum of
  - time and room assignment penalties
  - penalties of broken soft distribution constraints
  - the total number of student conflicts
- You can compare your results with competitors!
  - about 800 registrations from 80 countries

- https://www.itc2019.org
- *T. Müller, H. Rudová, Z. Müllerová, Real-world university course timetabling at the International Timetabling Competition 2019, Journal of Scheduling, 28(2): 247–267, 2025.*

Vehicle Routing

Freight Transportation Problem



Cooperation with company Wereldo

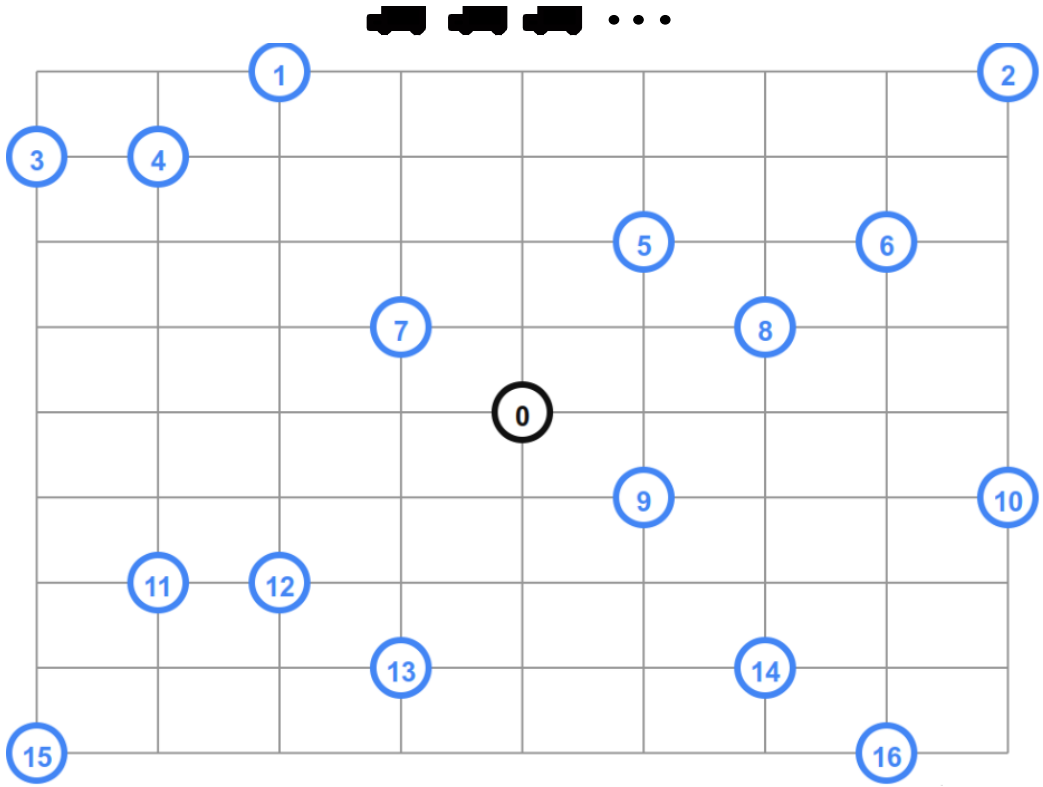
wereldo.com

- rich vehicle routing problem
- 200 pickup-delivery requests
- 20 trucks
- 200–370 km and
  7–9 hours per day and truck

- *V. Sassmann, H. Rudová, M. Gabonay and V. Sobotka (2023). Real-world vehicle routing using adaptive large neighborhood search. In EvoCop 2023, LNCS 13987, p. 34–49.*
- *V. Sobotka and H. Rudová, Uncertainty in Real-World Vehicle Routing. In ECAI 2024, p. 4311–4318.*

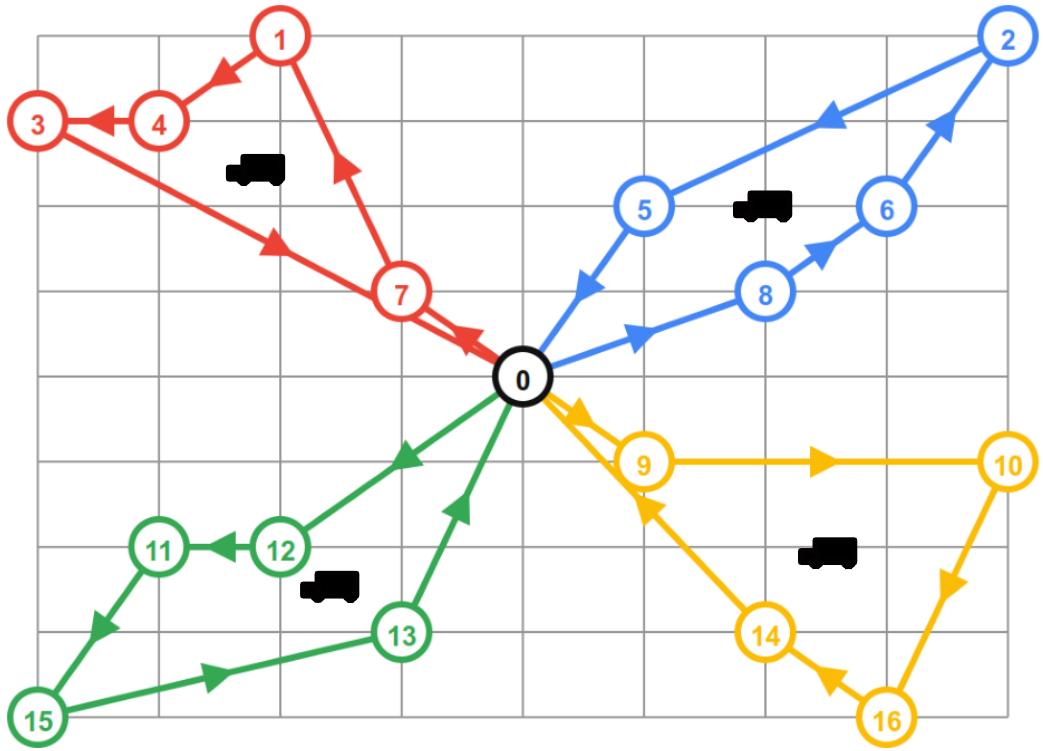
Vehicle routing problem (VRP)

- Requests
- Depot
- Vehicles



Vehicle routing problem (VRP)

- Requests
- Depot
- Vehicles
- Routes
  - serve all requests
  - minimize distance



Rich vehicle routing problem

Requests

- time windows
- joint service time
- weights & volumes
- pickup & deliveries
- request-vehicle compatibility

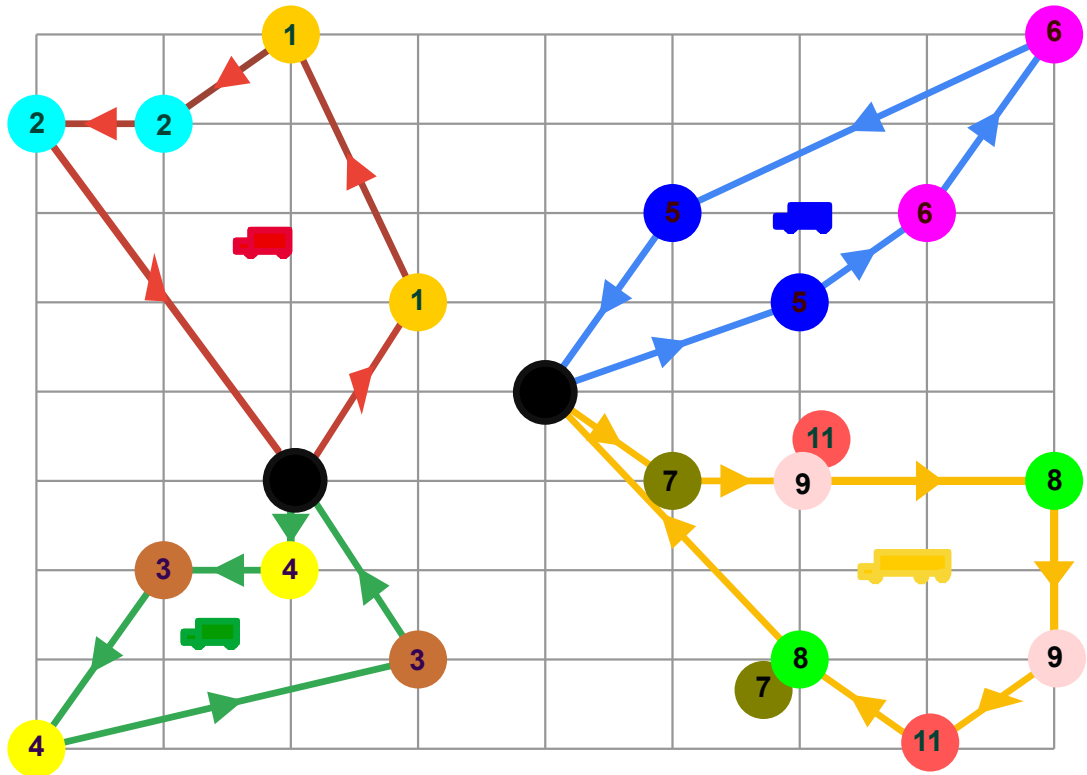
Vehicles

- multiple depots
- heterogeneous fleet

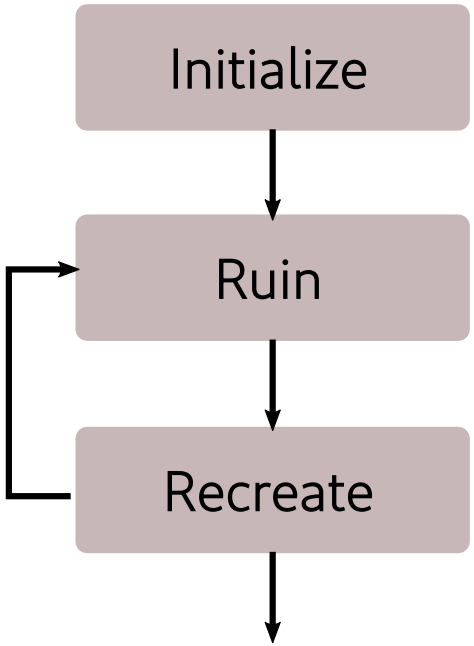
Routes

- route duration limit
- route length limit

...



Large neighborhood search (LNS)



1. Find an initial fesible solution

2. Select a part of the solution &
   Unassign its variables

3. Reoptimize the unassigned part &
   Keep the rest fixed

Ruin & recreate vs. destroy & repair

- *P. Shaw (1998). Using constraint programming and local search methods to solve vehicle routing problems. In Principles and Practice of Constraint Programming – CP98, 417–431. LNCS 1520, Springer.*

Ruin & recreate heuristics

Ruin heuristics

- random removal
- removal of worst requests based on cost
- Shaw removal: remove similar requests
  - idea: they can be easily exchanged together (in following recreate)

Ruin & recreate heuristics

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- random removal
- removal of worst requests based on cost
- Shaw removal: remove similar requests
  - idea: they can be easily exchanged together (in following recreate)

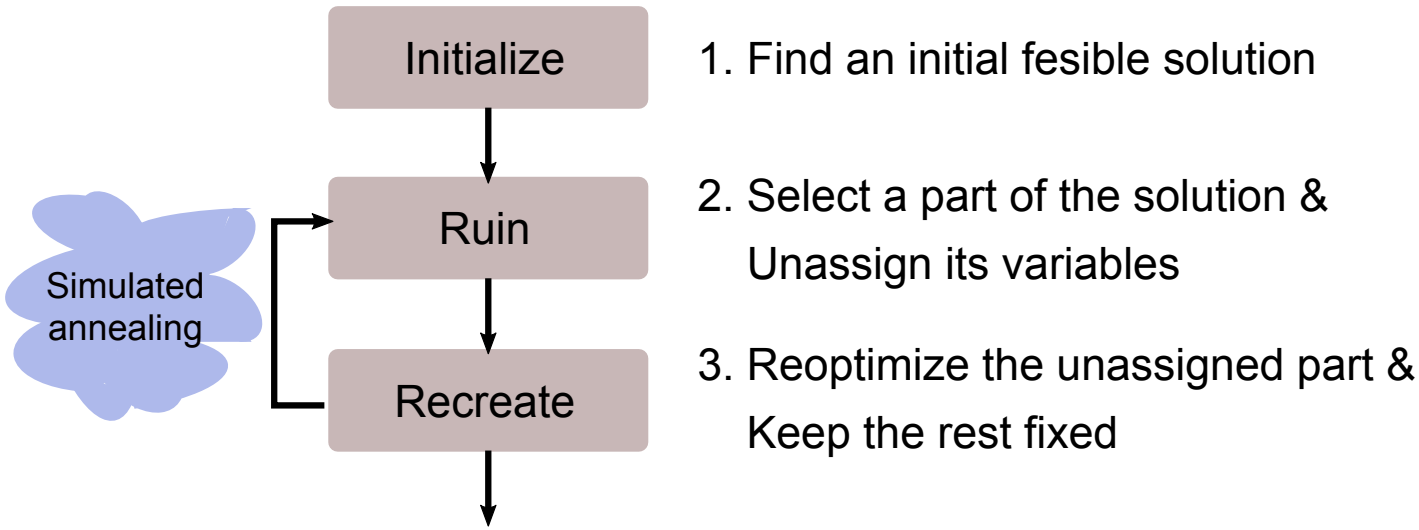
Recreate heuristics:

recompute costs each time

- greedy insertion heuristic
- regret insertion heuristic
  - it picks the request with the largest cost loss between its best and second best place
  - it then assigns that request to its best place to avoid regretting not having done that

Slack induction by string removals (SISRs)

- SISRs: large neighborhood search heuristic solver

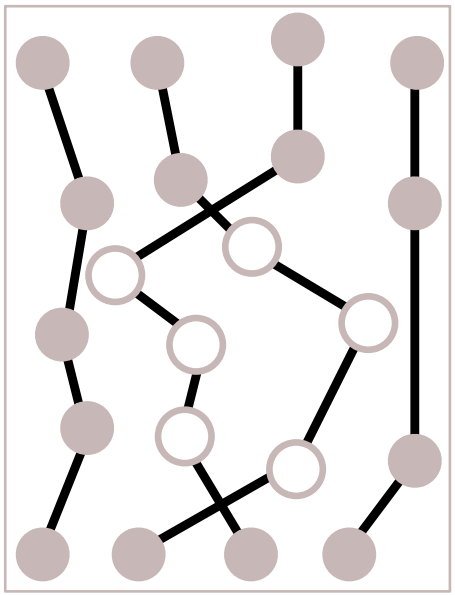


- Algorithmic simplicity and versatility w.r.t. problem variants
  - common algorithmic core
  - minimal adaptation to specific VRP variants

- *J. Christiaens and G. V. Berghe. Slack induction by string removals for vehicle routing problems. Transportation Science, 54:417–433, 2020.*

SISRs: Ruin phase

- Core idea: introduce capacity & spatial slacks
- Remove continuous strings of customer requests within routes
- Strings from two routes should be close to each other, i.e., adjacent



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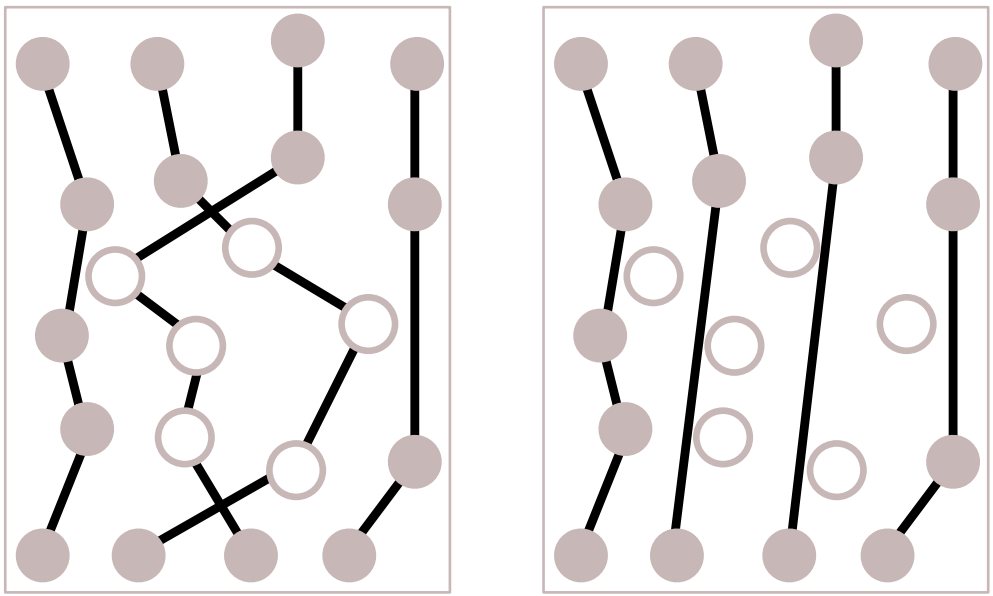

- Ruin phase $\Rightarrow$ a set of absent customer requests A

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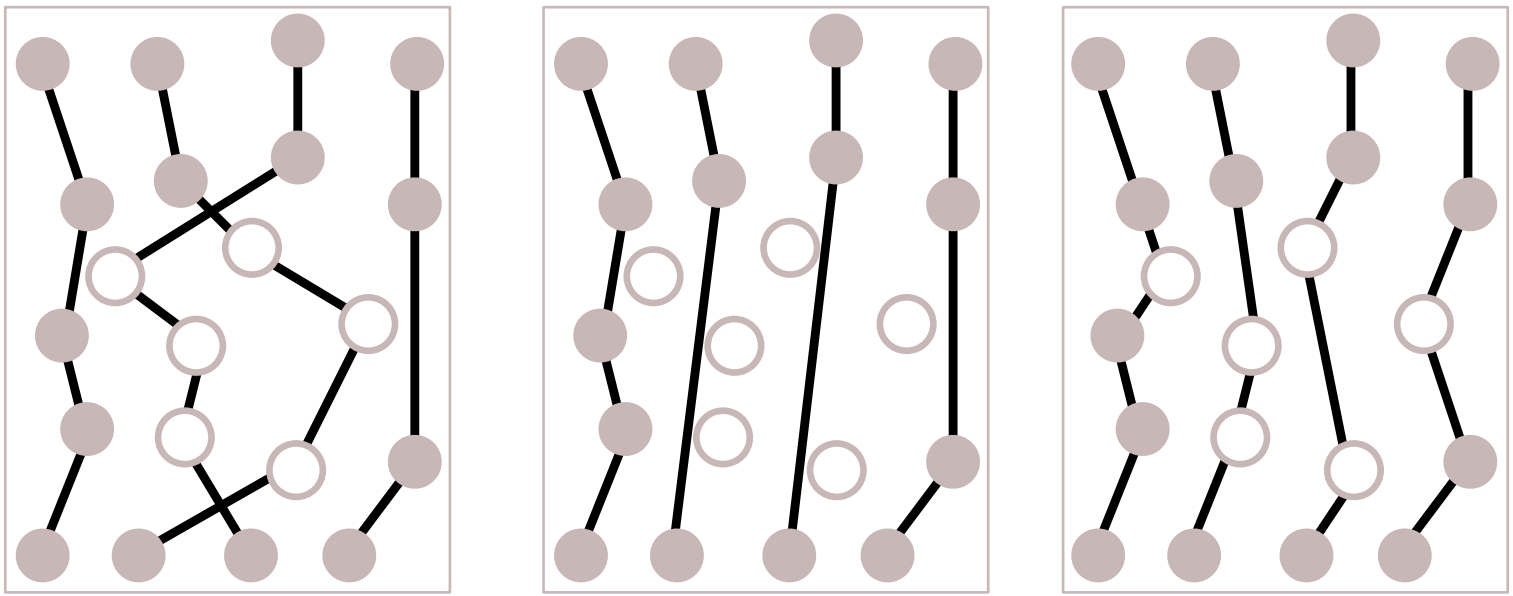
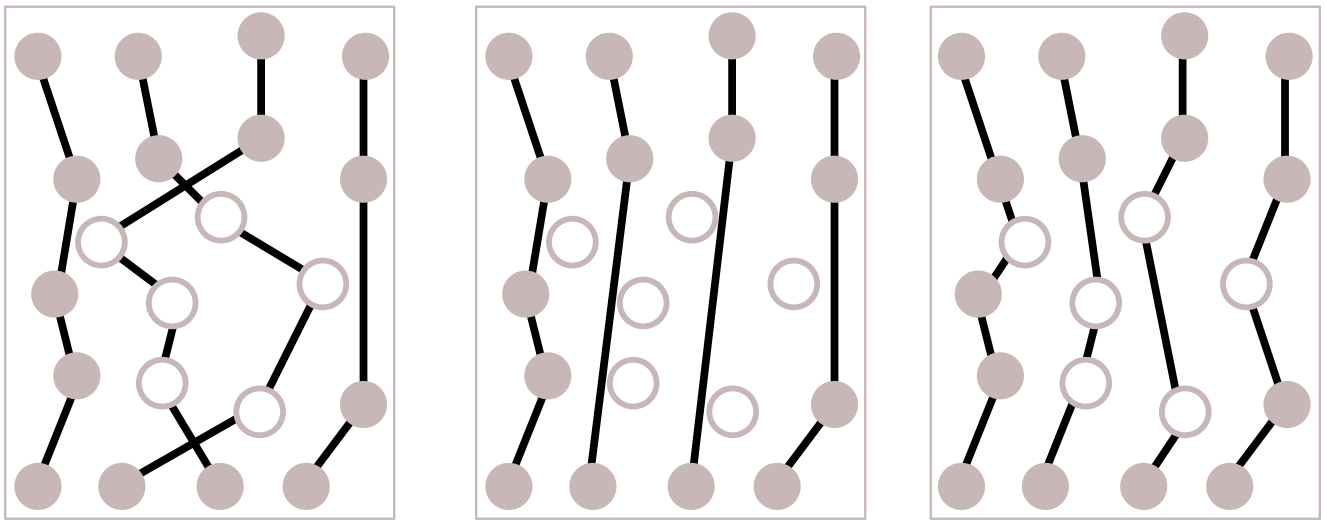


- Ruin phase $\Rightarrow$ a set of absent customer requests A

SISRs: Recreate phase by sorting

- Examples of sorting criteria
  - customer demand, descending
  - time window width, ascending
  - simple random shuffling
- Randomly select one sorting criterion & sort absent requests A
  - sorting criteria weights
- Reinsert customer requests from sorted A one-by-one
  - cheapest insertion based on distance, blinks

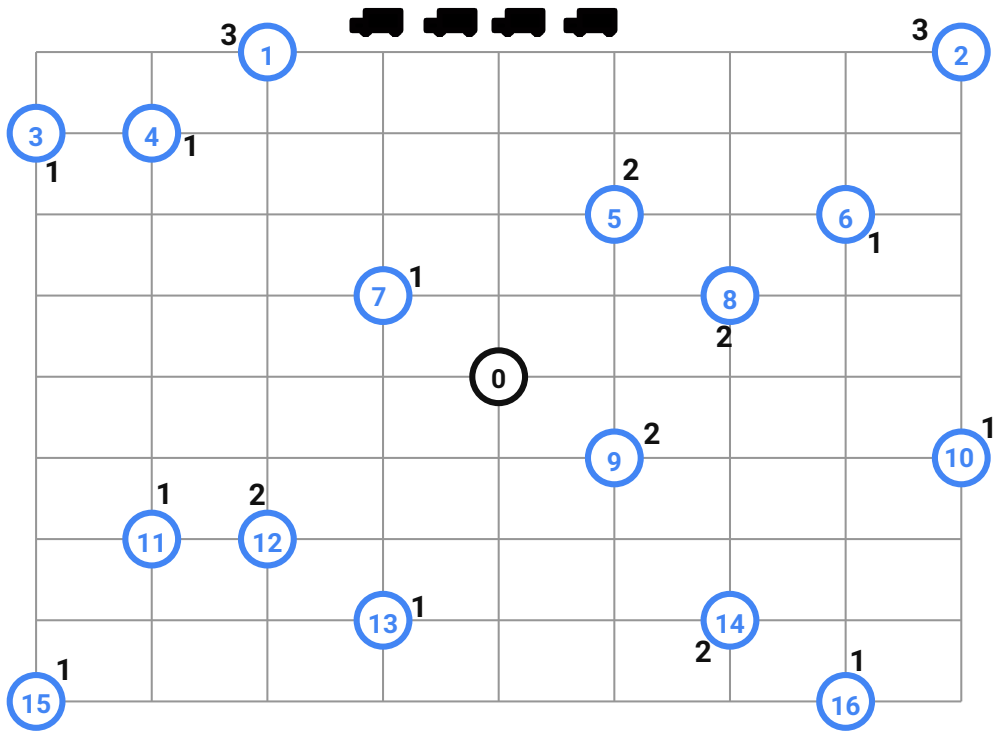


SISRs on top of LNS

- SISRs ruin: strings & slack
- LNS recreate
  - each request placed in a position with the smallest increase in cost
  - recompute cost for each customer request
- SISRs recreate: sorting
  - compute insertion costs at the beginning
  - reinsert sorted customer requests one-by-one
  - sorting adjusted for the problem
    - based on capacity, time windows, score of customers
- Simplified process sufficient!
  - smaller complexity

Team orienteering problem (TOP)

- Requests
- Score of request
- Depot
- Limited number of vehicles
- Routes
  - minimize distance
  - maximize the total score of served customers



- Various problem variants
  - base TOP, capacities CTOP, time windows TOPTW, ...

Team orienteering problem (TOP)

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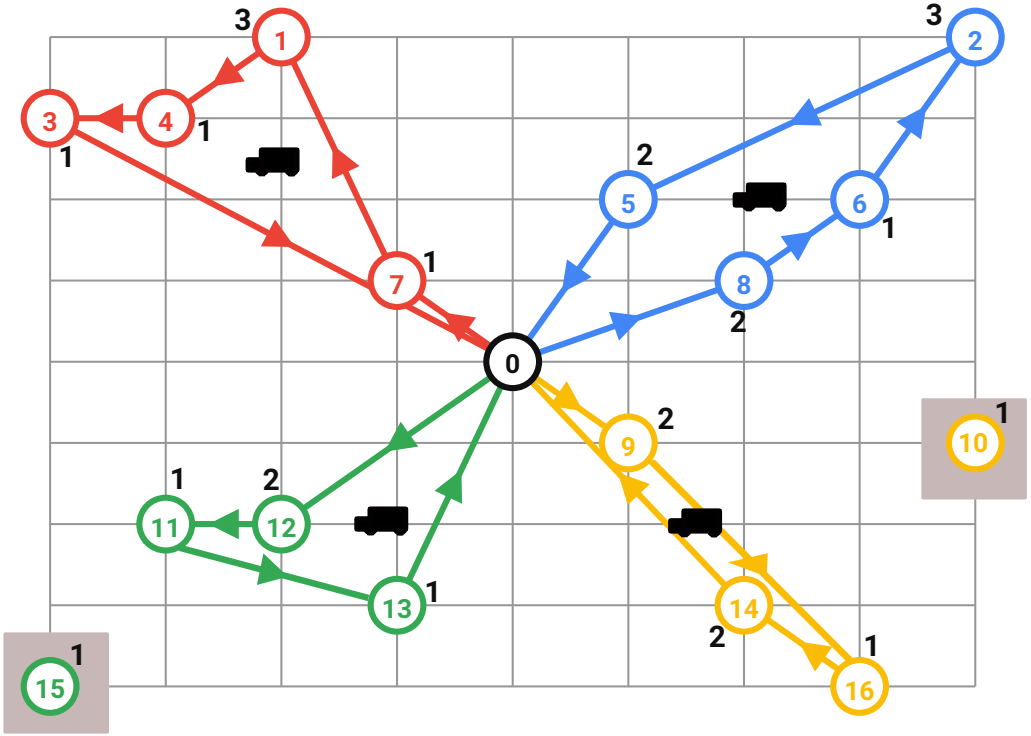
  - route length limit



- Various problem variants
  - base TOP, capacities CTOP, time windows TOPTW, ...

SISRs for TOPs

- Our extension of SISRs for TOPs
  - essential: new sorting methods for recreate
- Experimental comparison with state-of-the-art methods
  - for TOP, TOPTW, CTOP
  - standard benchmarking datasets and experimental setups
- TOP & TOPTW: performance on par with state-of-the-art methods
- CTOP: benchmarks dominated by our SISRs adaptation
- Overall: found $\sim$ 85 % of all best-known solutions
- SoTA approach: HALNS for TOP & CTOP
  - combines ALNS with exact integer programming to solve sub-route optimization and set packing problems

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- *M. Pajerský, V. Sobotka, and H. Rudová. Open-Source Implementation of Slack Induction by String Removals for Routing and Orienteering Problems. In CPAIOR 2026, p. 359–377.*

Open-source implementation of SISRs solvers

`https://github.com/hankarudova/open-source-sisr-routing`

- *M. Pajerský, V. Sobotka, and H. Rudová. Open-Source Implementation of Slack Induction by String Removals for Routing and Orienteering Problems. In CPAIOR 2026, p. 359–377.*

Cross-Domain Search

Hyper-heuristics

Main idea: automatically construct the search algorithm

Selection hyper-heuristics: adaptive selection of low level heuristics

Search operators ≈ low-level heuristics (LLHs)

- local search
  - neighborhood-based search moves
  - guarantee of non-worsening solutions
- perturbative heuristics
  - ruin & recreate
  - mutation
- crossover
  - recombination of two solutions

Online selection cross-domain hyper-heuristics

Characteristics

- online: the algorithm is constructed as it searches
- selection: adaptive selection of LLHs
- cross-domain: aim to perform well across diverse problem domains

Broad range of approaches & algorithms

- variable-neighborhood search, iterated local search, evolutionary approaches, Monte Carlo tree search, reinforcement learning, ...

- *Drake, J.H., A. Kheiri, E. Özcan, E.K. Burke (2020). Recent advances in selection hyper-heuristics, EJOR, 285(2):405–428.*
- *Razali, M. K. M., Ayob, M., Rahman, A. H. A., Jarmin, R., Liu, C. Y., Maaya, M., Izaham, A., and Kendall, G. (2025). Unveiling effective heuristic strategies: A review of cross-domain heuristic search challenge algorithms. CMES, 142(2):1233–1288.*
- *Burke, E. K., Gendreau, M., Hyde, M., Kendall, G., McCollum, B., Ochoa, G., Parkes, A. J., and Petrovic, S. (2011). The cross-domain heuristic search challenge—an international research competition. In LION, 631–634.*

How to select vs. what to select from

- Prevailing assumptions: the provided LLH set is fixed and used as is
- Key focus: how to select LLHs
  - e.g., involved reinforcement-learning-based selection

- Our focus: what LLHs to select from
  - idea: transform the LLH set and operate on the transformed LLH set
  - goal: control critical properties of LLHs and improve cross-domain performance

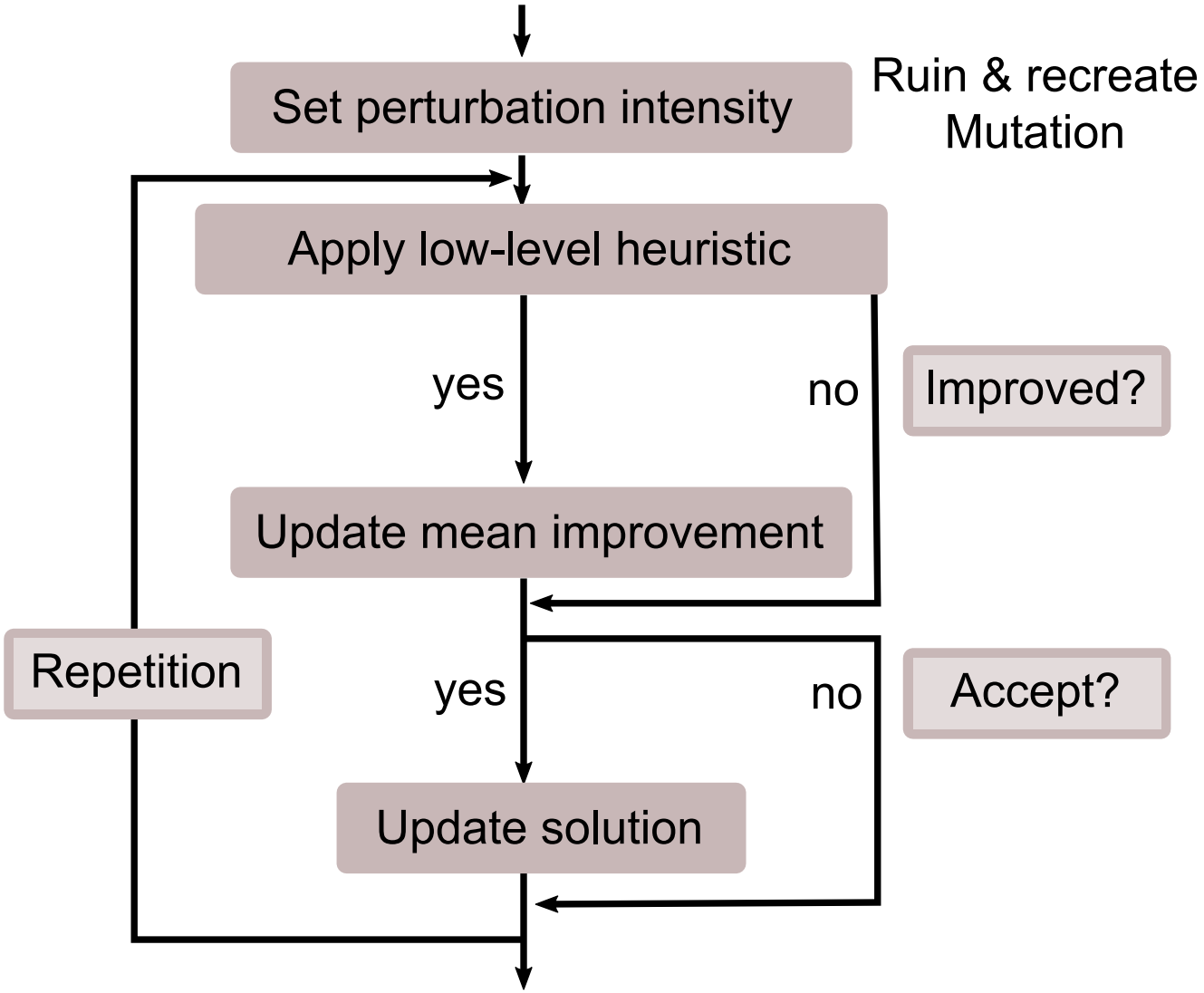
Key principles in cross-domain search

The search process should operate in a reasonably safe environment (1) with normalized granularity at which new LLHs are sampled (2), while allowing the perturbation intensity to vary (3).

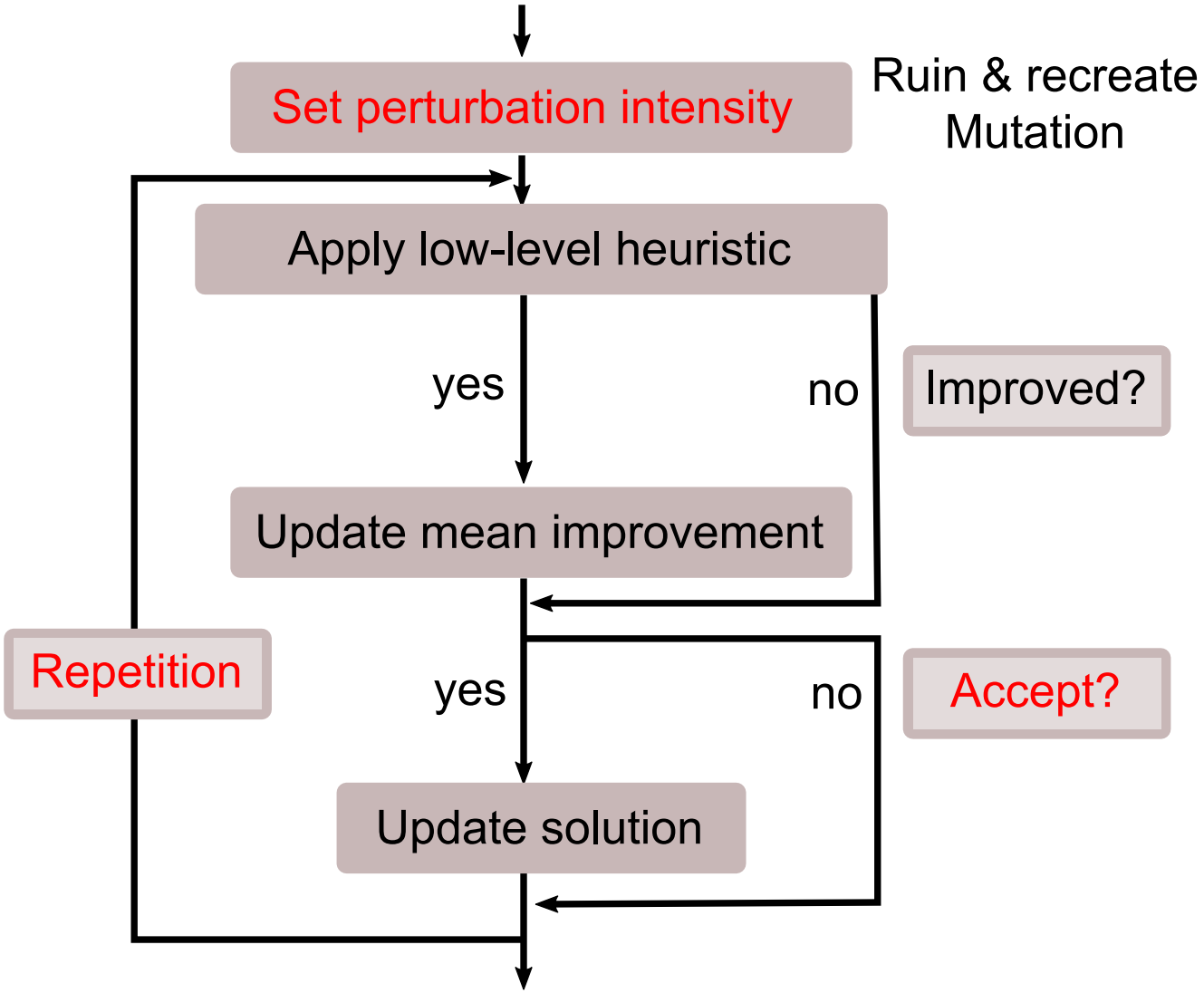
1. Solution acceptance
   - balance between intensification and diversification
2. Repetitions
   - fairness in time-allocation among LLHs
3. Perturbation intensity
   - balance between intensification and diversification

- *V. Sobotka, L. Kletzander, N. Musliu, and H. Rudová (2025). Key Principles in Cross-Domain Hyper-Heuristic Performance. Pre-print at arXiv.org.*

Hyper-heuristics



Hyper-heuristics: Key principles



Naive hyper-heuristic

Start with a naive hyper-heuristic

- uniformly random selection of an LLH category
  - local search, ruin & recreate, mutation, crossover
- and then uniformly random selection of an LLH within the category
- while always accepting worse solutions

Naive hyper-heuristic & LLH set transformation

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- uniformly random selection of an LLH category
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Key principles

- varying perturbation intensity for each low-level heuristic
  - each perturbative LLH replaced by a set of LLHs based on a predefined set of intensities
- time-limited repetition of each low-level heuristic
  - original LLH replaced with a new LLH enforcing repetition timeout
- acceptance based on regular mean improvement updates

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LLH set transformation: acceptances + repetitions + intensities

- extend the NHH with LLH transformation: NHH*
- extend an existing hyper-heuristic X with LLH transformation: X*

HyFlex benchmark

- Cross-domain heuristic search competition 2011 (CHeSC)
- Standard benchmark for hyper-heuristics
- 6 problem domains
  - MAXSAT
  - binpacking
  - personnel scheduling
  - flowshop
  - traveling salesman problem
  - vehicle routing problem

- *Burke, E. K., Gendreau, M., Hyde, M., Kendall, G., McCollum, B., Ochoa, G., Parkes, A. J., and Petrovic, S. (2011). The cross-domain heuristic search challenge—an international research competition. In LION, 631–634.*

State-of-the-art hyper-heuristics

- Genetics with a large number of adaptive mechanisms (GIHH) [1]
  - winner of the original competition
- Lean GIHH [2]
  - simplified variant of original GIHH
- Fair share iterated local search (FSILS) [3]
  - simple hyper-heuristic outperforming [1]
- Thompson sampling iterated local search (TSILS)[4]
  - currently the best reported results

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[1] Mısır, M., Verbeeck, K., De Causmaecker, P., Vanden Berghe, G. An Intelligent Hyper-Heuristic Framework for CHeSC 2011. In Learning and Intelligent Optimization (LION), 2012.

[2] Adriaensen S. and Nowé A. Case Study: An Analysis of Accidental Complexity in a State-of-the-art Hyper-heuristic for HyFlex. In Evolutionary Computation (CEC), 2016.

[3] Adriaensen, S., Brys, T., and Nowé, A. Fair-share ILS: a simple state-of-the-art iterated local search hyperheuristic. In Annual Conference on Genetic and Evolutionary Computation (GECCO), 2014.

[4] S. A. Adubi, O. O. Oladipupo and O. O. Olugbara. Configuring the Perturbation Operations of an Iterated Local Search Algorithm for Cross-domain Search: A Probabilistic Learning Approach. In Congress on Evolutionary Computation (CEC), 2021.

Reinforcement learning hyper-heuristics

- Monte Carlo reinforcement learning hyper-heuristic (MC) [1]
- Large-state reinforcement learning with iterated local search (LASTRL) [2]
- Q-learning to select LLH and acceptance (QHH) [3]

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[1] Mischek, F., and Musliu, N. Reinforcement learning for cross-domain hyper-heuristics (2022). In International Joint Conference on Artificial Intelligence (IJCAI).

[2] Kletzander, L., and Musliu, N. Large-state reinforcement learning for hyper-heuristics (2023). In Proceedings of the Thirty-Seventh AAAI Conference on Artificial Intelligence and Thirty-Fifth Conference on Innovative Applications of Artificial Intelligence and Thirteenth Symposium on Educational Advances in Artificial Intelligence. AAAI Press.

[3] Choong, S. S., Wong, L.-P., and Lim, C. P. (2018). Automatic design of hyper-heuristic based on reinforcement learning. Information Sciences, 436–437:89–107.

LLH set transformations: Raw power

- HyFlex benchmark
- F1 score
  - classical Formula 1 ranking used for comparison of hyper-heuristics
- NHH: unbiased random LLH selector
  $\Rightarrow$ 0 F1 points
- NHH*: NHH controlled LLH set

Rank	Method	F1 score
1.	TSILS*	105
2.	GEPHH	97
3.	LGIHH*	91
4.	FSILS*	79
5.	LGIHH	79
6.	MC*	78
7.	TSILS	76
8.	FSILS	74
9.	LUBY*	68
10.	MCTS	65
11.	**NHH***	**57**
12.	EAILS*	50
13.	MC	48
14.	GIHH	33
15.	ML	29
16.	EAILS	28
17.	LASTRL	28
18.	LUBY	27
19.	QHH	23

LLH set transformations: Raw power

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- Compare:
  - NHH* vs. GIHH

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- Compare:
  - NHH* vs. GIHH
  - NHH* vs. recent RL-based methods

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LLH set transformations: Other hyper-heuristics

- Many other hyper-heuristics extended by LLH set transformation:
  - MC, LUBY
  - LGIHH, FSILS, TSILS, EAILS
    - added only intensities
- Compare:
  - TSILS vs. TSILS*

Rank	Method	F1 score
1.	**TSILS***	**105**
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3.	LGIHH*	91
4.	FSILS*	79
5.	LGIHH	79
6.	MC*	78
7.	**TSILS**	**76**
8.	FSILS	74
9.	LUBY*	68
10.	MCTS	65
11.	NHH*	57
12.	EAILS*	50
13.	MC+	48
14.	GIHH	33
15.	ML	29
16.	EAILS	28
17.	LASTRL	28
18.	LUBY+	27
19.	QHH	23

LLH set transformations: Other hyper-heuristics

- Many other hyper-heuristics extended by LLH set transformation:
  - MC, LUBY
  - LGIHH, FSILS, TSILS, EAILS
    - added only intensities
- Compare:
  - TSILS vs. TSILS*
  - LGIHH vs. LGIHH*
  - ...

Rank	Method	F1 score
1.	TSILS*	105
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Real-world domains

- Developed LLH set transformations tested on 3 real-world domains
- Rich pickup and delivery problem
- Minimum shift design
- Bus driver scheduling
- Comparison of available hyper-heuristics
  - X and X* variants using the developed LLH set transformations
- Comparison to problem-specific methods and state-of-the-art results

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- *Sassmann, V., H. Rudová, M. Gabonay and V. Sobotka (2023). Real-world vehicle routing using adaptive large neighborhood search. In EvoCop 2023, LNCS 13987, p. 34–49.*
- *Kletzander, L. and Musliu, N. (2024). Hyper-heuristics for personnel scheduling domains. Artificial Intelligence, 334:104172.*

Results on real-world domains

- Key trends same as for benchmarks:
  - $X^* \gg X$
  - exception: FSILS vs. FSILS*
- Simplicity common to top 3 methods
  - FSILS, NHH* by design
  - TSILS* simplified from TSILS
- 35 new best-known solutions (BKS)
  - 24/10/1 BKSs: X^*/X/shared

Rank	Method	F1 score
1.	**TSILS***	**306**
2.	**FSILS**	**303**
3.	**NHH***	**301**
4.	EAILS*	276
5.	LGIHH*	271
6.	TSILS	228
7.	EAILS	209
8.	MC*	205
9.	LGIHH	196
10.	LUBY*	166
11.	FSILS*	129
12.	MC$^+$	98
13.	LUBY$^+$	83

Discussion

Transformation of the low-level heuristics' set

- improved cross-domain performance for many recent hyper-heuristics

Design simplicity is your friend

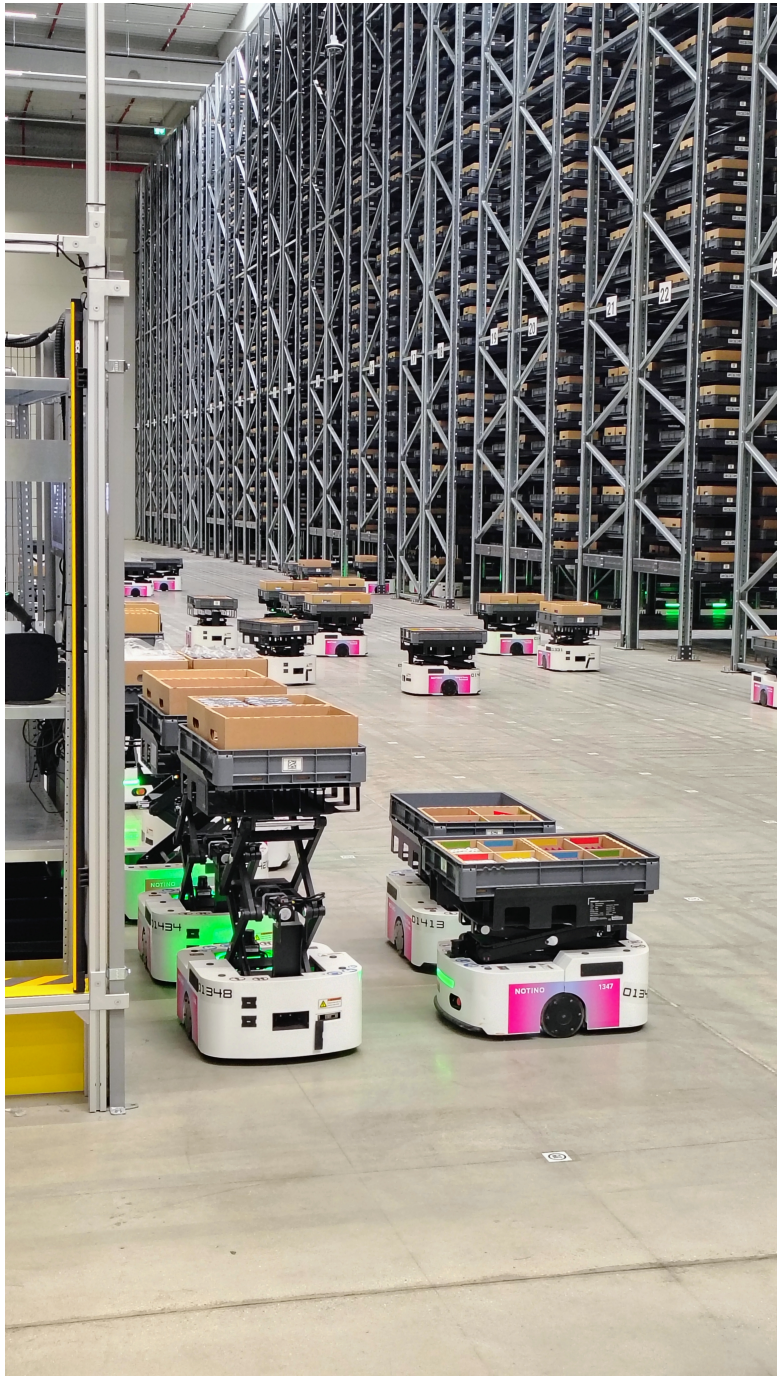
- performance of NHH*
- LGIHH vs. GIHH
- FSILS
- TSILS, EAILS vs. TSILS*, EAILS*

. . . especially on real-world problems

Trivial selection mechanism: new best-known results

- comparable or even outperforming recent hyper-heuristics

Warehouse Planning



Warehouses of Notino company

Real-world problems

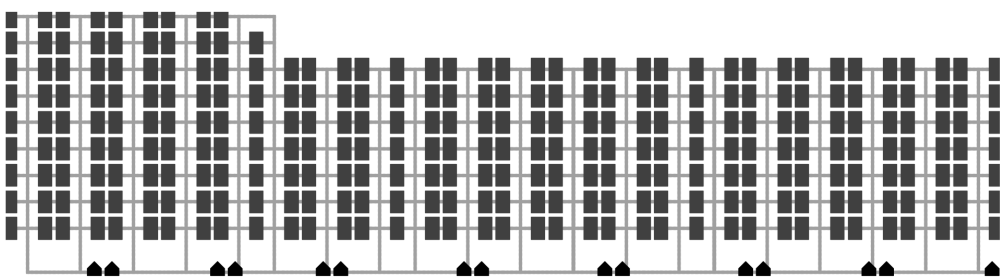
Manual picker-to-parts warehouse

NOTINO

- pickers walk through pick locations of orders
- warehouse in Czech Republic
- on average $50,000$ / up to $160,000$ orders per day
- 3.5 products per order

Robotic parts-to-picker warehouse

- parts (products) moved to pickers by automated systems (robots)
- warehouse in Romania
- $10,000$ – $23,000$ orders per day
- 4.5 products per order



Real-world vs. generated data

- streams of orders

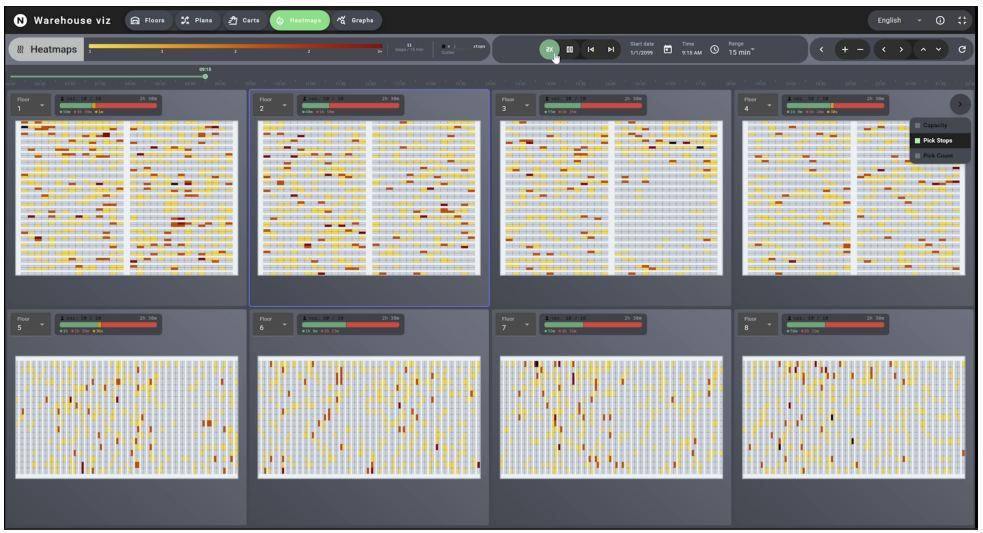
Simulation of warehouse processes

Simulation environment

- storage assignment: how to distribute storage across warehouse
- order processing: which orders to jointly process per picking tour

Planning algorithms for particular processes

- order batching into pickboxes, item position selection, routing, ...
- study of their interactions



Performance metrics

- lateness for orders
- throughput of warehouse

Order batching into pickboxes

- simple hill climbing improved performance significantly
- better than a higher complexity approach

Conclusion

Acknowledgements

Václav Sobotka, Robert Zvara

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Michal Gabonnay, Tomáš Zahradník

Martin Kavřík, Ondřej Hastík, Ksenia Shakurova

Elegance of simplicity

Real-world problems

- course timetabling
- vehicle routing
- warehouse planning

This presentation:

Elegance of simplicity

Real-world problems

- course timetabling
- vehicle routing
- warehouse planning

Can you simplify your methodology?

- by design?
- by generalization?
- by complexity?

Can you make it more elegant?

This presentation:

Contents