# Combined Vehicle Routing and Crew Scheduling with Hours of Service Regulations

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# Motivation

Frankfurt
Hannover
Dortmund
66
Diedenbergen
Gewerbegebiet
Wallau
120
GRUMMEL
Platz da!
Source: VDStra

# Hours of service regulations – single manning

In the European Union a single truck driver must:

- take a break of at least 45 minutes after at most four and a half hours of driving,
- take a rest of at least 11 hours after at most nine hours of driving,
- take the required rest within 24 hours after the end of the previous rest.

# Hours of service regulations – single manning

A driver may take breaks and rest periods in two parts:

- The first part of the break must have a duration of at least 15 minutes and the second part of at least 30 minutes.
- The first part of the rest must have a duration of at least three hours and the second part of at least nine hours.

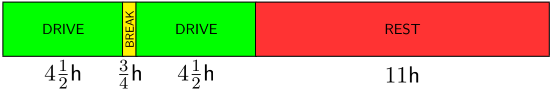
# Hours of service regulations – double manning

If a vehicle is continuously manned by a team of two drivers, one driver can take a break while to other is driving.

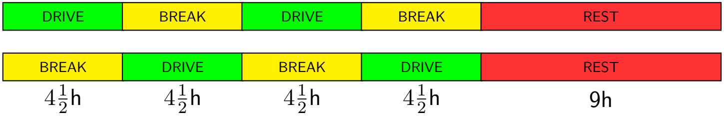
- The minimum duration of a rest period for team drivers is 9 hours and rest periods must be taken by both drivers at the same time.
- The required rest must be taken within 30 hours after the end of the previous rest.

# Hours of service regulations

Vehicle manned by one driver:




Vehicle manned by two drivers:

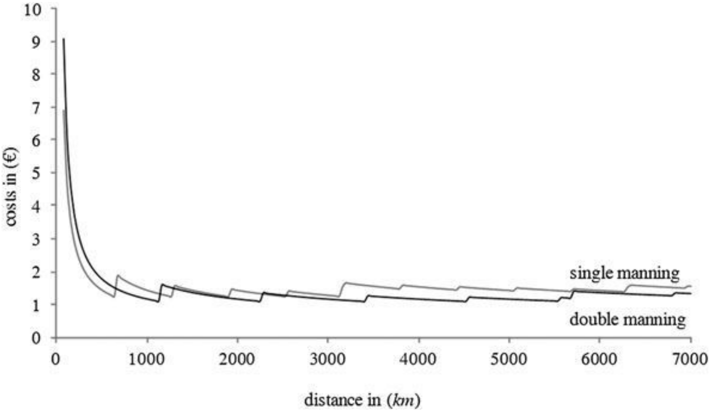


# Hours of service regulations

So far team driving has not yet been studied in a vehicle routing context.

- Goel and Kok (2012) model the EU regulations for team drivers and develop an algorithm for efficiently scheduling working hours of team drivers.
- Kopfer and Buscher (2015) analyse EU regulations for team drivers and compare the efficiency of team driving versus single manning.

# Hours of service regulations



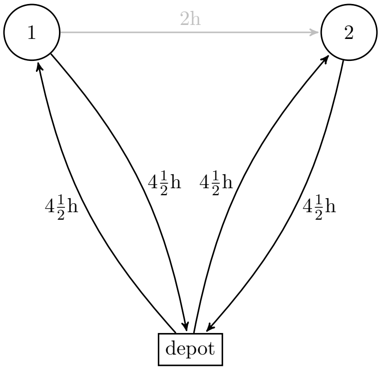

Source: Kopfer and Buscher (2015)

# Hours of service regulations

- Kopfer and Buscher (2015) conclude that team driving is more cost efficient compared to single driving for trips of 9 hours of driving or above with the exception of trips of 16 to 18 hours driving.
- One major limitation is that this analysis does not take into account that transport companies can optimise routes and schedules to combine single and double manning in the most effective way.

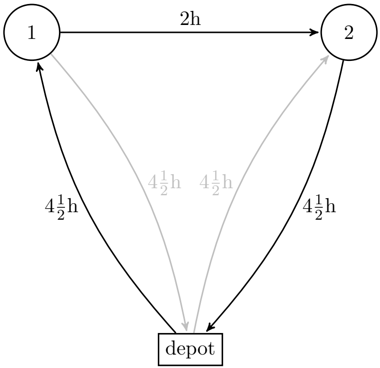
# Hours of service regulations

**Single manning**



# Hours of service regulations

**Team driving**



# Contents

# Combined vehicle routing and crew scheduling

- Company seeks to optimize crew compositions, routes and schedules for a complex less-than-truckload routing application with team drivers.
  - Aiming to solve the complete integrated problem.
  - Some teams accepting to work on separate itineraries when needed.
- Additional research goal ⇒ how different pricing scenarios (fuel, wages, trucks) impact the distribution of single drivers and teams.

# Combined vehicle routing and crew scheduling

- Problem to address : "team mix" vehicle routing and truck driver scheduling problem. **Objective function** based on:
  - Amortized cost of a vehicle $c^{\text{FLEET}}$ and driver wages $c^{\text{DRIVER}}$ per time period (e.g., day in the week).
  - Mileage costs $c^{\text{MILEAGE}}$

$$\min \sum_{r \in R_1} \{(c^{\text{FLEET}} + c^{\text{DRIVER}}) \times d_r^{\text{SINGLE}} + c^{\text{MILEAGE}} k_r\} \, y_r \tag{2.1}$$

$$+ \sum_{r \in R_2} \{(c^{\text{FLEET}} + 2c^{\text{DRIVER}}) \times d_r^{\text{TEAM}} + c^{\text{MILEAGE}} k_r\} \, y_r \tag{2.2}$$

$$\text{s.t.} \sum_{r \in R_1 \cup R_2} a_{nr} y_r = 1, \qquad n \in \{1, \ldots, n\} \tag{2.3}$$

$$y_r \in \{0, 1\}, \qquad r \in R_1 \cup R_2 \tag{2.4}$$

  - Time windows + HOS regulations + possibility to delay the time period for departure so as to reduce costs.

# Contents

# Heuristic search of routes

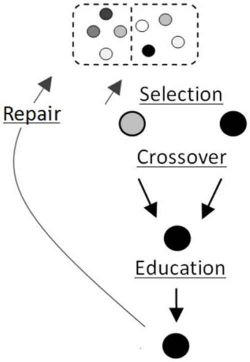
- Solution approach combining established techniques from previous research:
  - Unified Hybrid Genetic Search (UHGS) (Vidal et al., 2012, 2014)
  - Truck Driver Scheduling algorithms (Goel, 2010; Goel and Kok, 2012; Goel and Vidal, 2014)

# Heuristic search of routes

### UHGS

Classic genetic algorithm components: population, selection, crossover, and

1. Efficient **local-improvement** procedure. Replaces random mutation
2. Management of **penalized infeasible solutions**
3. Individual evaluation: **solution quality** and **contribution to population diversity**



# Heuristic search of routes

Local improvement procedure based on standard neighborhoods:

- RELOCATE, SWAP, CROSS, 2-OPT and 2-OPT*.
  - Exploration in random order
  - First improvement policy
  - Restrictions of moves to K$^{\text{TH}}$ closest customers
    $\Rightarrow$ Number of neighbors in $\mathcal{O}(n)$

**Penalized infeasible solutions:** Simple linear combination of the load excess and lateness

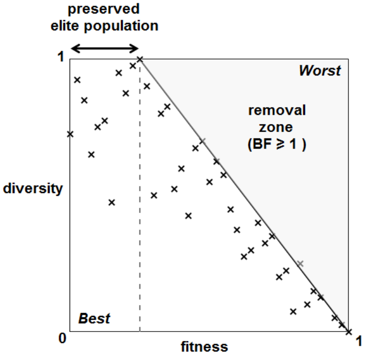
- Penalty coefficients are adapted during the search.

# Heuristic search of routes

**Biased fitness:** combining ranks in terms of solution cost $C(I)$ and contribution to the population diversity $D(I)$, measured as a distance to other individuals :

$$BF(I) = C(I) + \left(1 - \frac{nbElite}{popSize - 1}\right) D(I)$$

- Used for parents selection
  - ⇒ Balancing quality with innovation to promote a more thorough exploration of the search space.
- Used during selection of survivors
  - ⇒ Removing individuals with worst $BF(I)$ still guarantees elitism



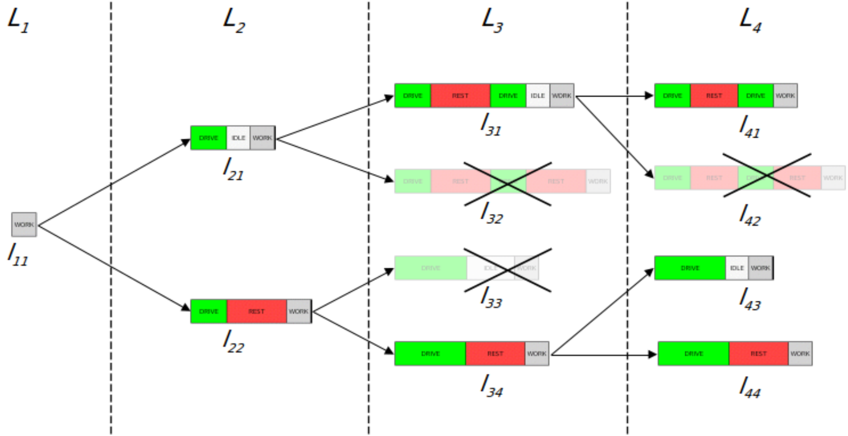
# Route evaluations

- **For all routes generated by the hybrid genetic search** $\Rightarrow$ determine whether the route can be feasibly operated by a single driver and/or a team of two drivers as well as the minimum number of time periods (days)
- Relying on scheduling procedures based on **labeling and tree search techniques**.
- Each route is evaluated two times: for single and team driving. $\Rightarrow$ Best cost is kept as route evaluation.

# Forward labelling

- Forward labeling method: the driver state is represented by a tuple of attributes indicating the degree to which the driver has already operated w.r.t. the regulatory limits (Goel, 2010; Goel and Kok, 2012).
- Each label is extended considering all reasonable alternatives of scheduling on- and off-duty periods.
- Dominance rules to reduce the number of alternative labels.
- To also evaluate infeasible intermediate solutions, allow late arrivals to customers with a linear penalty
  $\Rightarrow$ and use a strong dominance based on lateness.

# Forward labelling



# Start time optimisation

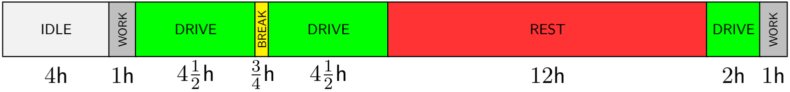
- A schedule with minimal duration can be generated using additional label attributes indicating by how much the start time of each schedule can be increased (Goel, 2012).
- To minimise the number of paid days, check at the end whether the start time of the schedule can be increased until the start of the next paid day.
  - NB – the "continuous" duration of the schedule spanning the smallest number days may not be the smallest

# Start time optimisation

Waiting time scheduled before work period:


Rest extended to avoid idle time:


Start time postponed:



# Speed-up techniques

- 1) **Labels pre-processing:** for both scheduling algorithms, pre-process the labels starting from the depot.

- 2) **Move filters:**
  - Let $\bar{Z}(r)$ be a lower bound on the cost of a route $r$.
  - A move that modifies two routes: $\{r_1, r_2\} \Rightarrow \{r'_1, r'_2\}$ has a chance to be improving if and only if:

$$\Delta_{\Pi} = \bar{Z}(r'_1) + \bar{Z}(r'_2) - Z(r_1) - Z(r_2) < 0.$$

  - Use as lower bound the cost of a route as driven by a team, but paid as a single driver:

$$\bar{Z}(r) = \{(c^{\text{FLEET}} + c^{\text{DRIVER}}) \times d_r^{\text{TEAM}} + c^{\text{MILEAGE}} k_r\}$$

  - The scheduling algorithm for team driving is one order of magnitude faster (no need of split breaks and rests). This helps to filter many non-improving moves (70–95%) without need for both scheduling procedures.

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# Computational experiments

- Preliminary experiments conducted on benchmark instances for truck driver scheduling problems.
  - Planning horizon of 6 time periods (days)
  - Routes can space several days
  - Based on Solomon VRPTW test problems for $n = 100$
    $\Rightarrow$ Instances with different customer distributions: R1, C1, RC1
  - Time windows tightness from XXX% to YYY%

- All runs on a single Xeon 3.07 GHz CPU.
- Average of 5 runs per instance

# Computational experiments

- First experiment: **Impact of crew optimization on profitability**.
- Fixed cost parameters, relatively to mileage costs, driver wages and amortized truck costs from Kopfer and Buscher (2015):
  - driver cost $c^{\text{DRIVER}} = 140$ €
  - amortized truck cost (and maintenance) per day $c^{\text{FLEET}} = 300$ €
  - fuel costs $c^{\text{MILEAGE}} = 0.6$ € $\times$ distance

# Computational experiments

| | Optimized | Single-Only | | Team-Only | |
|---|---|---|---|---|---|
| C101 | 28716.95 | 29456.28 | 2.57% | 34530.77 | 20.25% |
| C102 | 25786.05 | 26078.19 | 1.13% | 29158.92 | 13.08% |
| C103 | 23153.07 | 23498.27 | 1.49% | 24352.75 | 5.18% |
| C104 | 19939.41 | 20884.02 | 4.74% | 20896.83 | 4.80% |
| C105 | 25122.62 | 25357.93 | 0.94% | 28797.18 | 14.63% |
| C106 | 25322.89 | 25573.62 | 0.99% | 28252.91 | 11.57% |
| C107 | 23561.77 | 24202.95 | 2.72% | 25849.20 | 9.71% |
| C108 | 22265.15 | 22564.39 | 1.34% | 24210.80 | 8.74% |
| C109 | 20222.91 | 20993.00 | 3.81% | 20593.02 | 1.83% |
| Avg C1 | | | **2.19%** | | **9.98%** |

# Computational experiments

| | Optimized | Single-Only | | Team-Only | |
|---|---|---|---|---|---|
| R101 | 30075.27 | 30560.96 | 1.61% | 32622.62 | 8.47% |
| R102 | 26671.20 | 27133.16 | 1.73% | 28895.40 | 8.34% |
| R103 | 22448.16 | 22709.16 | 1.16% | 24334.24 | 8.40% |
| R104 | 18605.24 | 19373.96 | 4.13% | 19277.08 | 3.61% |
| R105 | 23899.01 | 24619.50 | 3.01% | 24335.82 | 1.83% |
| R106 | 22006.64 | 22563.15 | 2.53% | 22774.82 | 3.49% |
| R107 | 19883.19 | 20449.98 | 2.85% | 20529.92 | 3.25% |
| R108 | 17542.49 | 18469.01 | 5.28% | 17751.41 | 1.19% |
| R109 | 19621.08 | 20791.05 | 5.96% | 19834.21 | 1.09% |
| R110 | 18250.05 | 19364.28 | 6.11% | 18383.01 | 0.73% |
| R111 | 18912.30 | 19678.16 | 4.05% | 19635.09 | 3.82% |
| R112 | 16876.99 | 17972.02 | 6.49% | 17116.41 | 1.42% |
| Avg R1 | | | **3.74%** | | **3.80%** |

# Computational experiments

| | Optimized | Single-Only | | Team-Only | |
|---|---|---|---|---|---|
| RC101 | 27929.56 | 28651.12 | 2.58% | 29259.82 | 4.76% |
| RC102 | 25685.83 | 26255.18 | 2.22% | 26426.18 | 2.88% |
| RC103 | 23828.85 | 24142.05 | 1.31% | 24882.85 | 4.42% |
| RC104 | 21177.15 | 22130.20 | 4.50% | 21204.49 | 0.13% |
| RC105 | 26468.75 | 27305.30 | 3.16% | 27809.62 | 5.07% |
| RC106 | 23393.07 | 24218.34 | 3.53% | 23586.13 | 0.83% |
| RC107 | 21369.05 | 22460.19 | 5.11% | 21565.87 | 0.92% |
| RC108 | 20370.87 | 21851.64 | 7.27% | 20505.37 | 0.66% |
| Avg RC1 | | | **3.71%** | | **2.46%** |
| Overall | | | **3.23%** | | **5.45%** |

# Computational experiments

| | Optimized | Single-Only | | Team-Only | |
|---|---|---|---|---|---|
| C201 | 19650.58 | 20409.93 | 3.86% | 20434.91 | 3.99% |
| C202 | 17152.42 | 18598.93 | 8.43% | 17448.70 | 1.73% |
| C203 | 15815.05 | 16044.98 | 1.45% | 16058.58 | 1.54% |
| C204 | 14521.94 | 15381.05 | 5.92% | 14828.20 | 2.11% |
| C205 | 15250.67 | 16464.96 | 7.96% | 15664.55 | 2.71% |
| C206 | 14678.29 | 15800.96 | 7.65% | 14929.53 | 1.71% |
| C207 | 14571.50 | 16057.67 | 10.20% | 14927.55 | 2.44% |
| C208 | 14436.87 | 15304.02 | 6.01% | 14641.08 | 1.41% |
| Avg C2 | | | **6.44%** | | **2.21%** |

# Computational experiments

| | Optimized | Single-Only | | Team-Only | |
|---|---|---|---|---|---|
| R201 | 26937.57 | 27215.34 | 1.03% | 27690.68 | 2.80% |
| R202 | 23962.18 | 24681.16 | 3.00% | 24658.49 | 2.91% |
| R203 | 20270.57 | 21175.85 | 4.47% | 20680.95 | 2.02% |
| R204 | 16608.08 | 17433.10 | 4.97% | 16804.23 | 1.18% |
| R205 | 21521.93 | 21995.78 | 2.20% | 21677.16 | 0.72% |
| R206 | 19750.70 | 20256.89 | 2.56% | 19698.07 | -0.27% |
| R207 | 17628.00 | 18723.27 | 6.21% | 17836.93 | 1.19% |
| R208 | 15781.74 | 16736.92 | 6.05% | 15854.95 | 0.46% |
| R209 | 19030.81 | 19917.09 | 4.66% | 19600.25 | 2.99% |
| R210 | 20325.14 | 21029.29 | 3.46% | 20894.78 | 2.80% |
| R211 | 17036.05 | 17600.22 | 3.31% | 17149.54 | 0.67% |
| Avg R2 | | | **3.81%** | | **1.59%** |

# Computational experiments

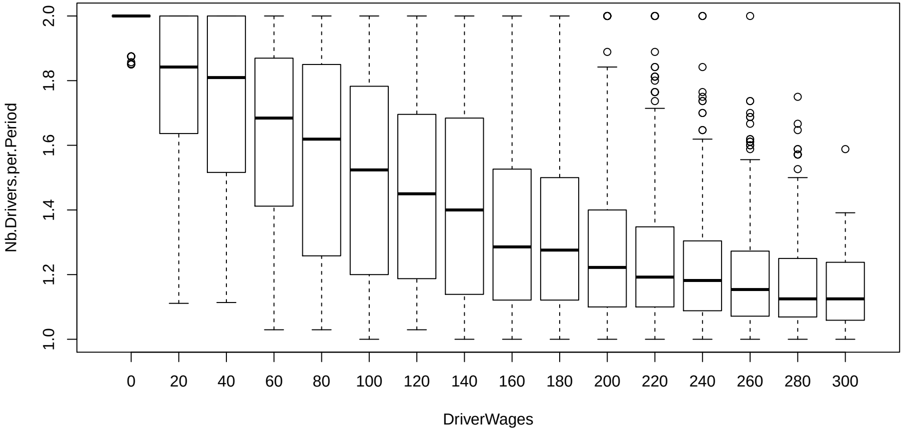
| | Optimized | Single-Only | | Team-Only | |
|---|---|---|---|---|---|
| RC201 | 29188.30 | 30577.84 | 4.76% | 29633.45 | 1.53% |
| RC202 | 25147.71 | 26628.66 | 5.89% | 25963.83 | 3.25% |
| RC203 | 21817.42 | 23244.64 | 6.54% | 22137.00 | 1.46% |
| RC204 | 17695.33 | 19331.83 | 9.25% | 18180.47 | 2.74% |
| RC205 | 26423.12 | 27919.91 | 5.66% | 26821.92 | 1.51% |
| RC206 | 23898.17 | 24384.89 | 2.04% | 24447.72 | 2.30% |
| RC207 | 21428.76 | 22447.47 | 4.75% | 21891.62 | 2.16% |
| RC208 | 17857.29 | 18417.05 | 3.13% | 17989.01 | 0.74% |
| Avg RC2 | | | **4.92%** | | **1.79%** |
| Overall | | | **5.02%** | | **1.88%** |
| Avg T(min) | 164.38 | 227.84 | | 99.91 | |

# Computational experiments

- Second experiment: **Assessment of main factors for crew decisions**.
- Varying the driver wages (wide range in Europe): $c^{\text{DRIVER}} \in \{0, 20, 40, 60, \dots, 300\}$
- Measuring the average number of drivers per truck and driven day.

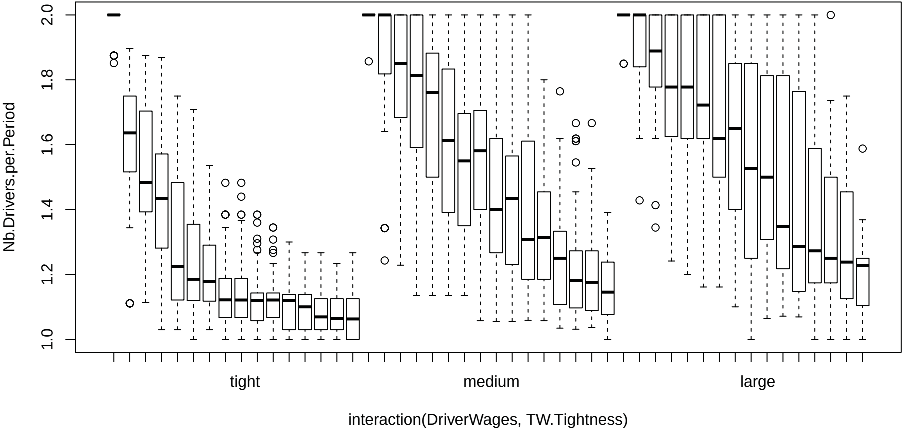
# Computational experiments

- Effect of driver wages on crew compositions:



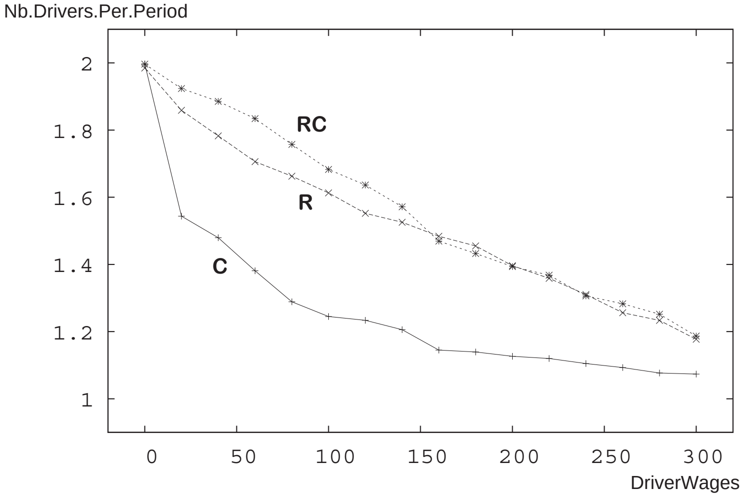
# Computational experiments

- Effect of driver wages on crew compositions, considering also the effect of time windows
  ⇒ Instances separated in three classes of TW width (small, medium, large) on sets ∪{R1, C1, RC1}



# Computational experiments

- Effect of driver wages and customers distribution on crew compositions



# Computational experiments

- **Other factors have a significant effect on crew decisions** and deserve further analysis:
  - **Tightness of the capacity constraints in the solutions** $\Rightarrow$ what is the current limiting resource (time or load)
  - Depot positioning
  - Third Cost dimension related to truck costs.

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# Conclusions

- Operating only single manned drivers is not the most competitive.
- Team drivers should not be used for all vehicles.
- Best strategy and potential for improvement depends on a number of instance characteristics
- From preliminary experiments, operational gains can be located anywhere in the range $[0, 15\%]$, significant savings are achievable for specific applications and cost ratios.

- Perspectives :
  - More insights to identify these “borderline applications”
  - In practice, even simpler algorithm or rules to choose single- or team-manning, getting 6% out of the theoretical 8% could help to move forward (without systematic need of the full UHGS+TDS algorithm).

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