Recent Research on Nurse Rostering at ASAP Group

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Recent Research on Nurse Rostering in ASAP

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ASAP Group, The University of Nottingham

automated scheduling research

Content

- Nurse rostering problems
  - Description & formulation
  - Brief literature review
  - Benchmarks
  - Related variants

- Recent approaches in ASAP
  - …

Nurse Rostering Problems

- Schedule a number of shifts to nurses in rosters, satisfying a set of constraints
  - Enough number of shifts (of different types) coverage on each day during the scheduling period
  - Side constraints
    - working/resting hours limit, complete weekends, skill levels, personal preferences, etc

Nurse Rostering Problems

- Hospitals operate 24/7, introduces constraints related to night shifts and weekends
- Different grade and skill mixes
- Number of shift types (early, day, late, night)
- Cover requirements can vary
- Long scheduling horizons and large numbers of employees

Nurse Rostering Problems

- Problems occur in hospital wards worldwide
- Difficult optimisation problem with many constraints and objectives
- Time consuming, frustrating and stressful problem
- Regular rescheduling required to cope with absences
- Poor planning and excess workload can cause decrease in quality of healthcare

Nurse Rostering Problems

- Automated nurse rostering
  - Satisfying more personal requests and preferences
  - Helps nurses plan their leisure time more effectively
  - Flexible schedules helps recruiting and retaining staff
  - Computers regarded as impartial

Nurse Rostering Problems

- Automated nurse rostering
  - Can ensure legal requirements are not broken
  - Lower costs e.g. hire less agency nurses to fill gaps in rosters
  - Distribute rosters via email and web
  - Generate management reports and statistics, connect to payroll systems, less paperwork etc

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Nurse Rostering Problems

	1							2							3							4							
December	04	05	06	07	08	09	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30	31	
	M	T	W	T	F	S	S	M	T	W	T	F	S	S	M	T	W	T	F	S	S	M	T	W	T	F	S	S	
1A	D	E	E	E	L			E	E	E	E		D	D	D	N	N	N				L	L	L	L				51
A	DH	DH	DH	DH	DH			DH	DH	DH		DH	DH	DH	DH		DH	DH				DH	DH	DH	DH	DH			20
B	N	N	N	N				D	D	L	L	L				L	L	L				E	E	E	D	D			0
C	D	D	D	D	D				N	N	N		L	L	L				L	L	L		E	E	E	L			25
D				L	N	N	N	N			DH	D				E	E	E	DH	E	E		N	N			E	E	13
E					D	DH	DH	D					E	E		DH	E	E	E	DH	DH		D	D	E	E	DH	DH	21
F	L	L	L			L	L	L	L			N	N	N	N			D	D			D				D	D	D	10
G				E	E	E	E			D	D	D			E	E			D	D	D	D			N	N	N	N	10
H	E	E	E			D	D		E	E	E	E			D	D	D		N	N	N	N					L	L	26

Total Penalty 176

Unassigned Shifts 0

Minimum Cover

E	1	2	2	2	1	1	1	1	2	2	2	1	1	1	1	2	2	2	1	1	1	1	2	2	2	1	1	1	
D	2	1	1	1	2	1	1	2	1	1	1	2	1	1	2	1	1	1	2	1	1	2	1	1	1	2	1	1	
DH	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	
L	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	
N	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	

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Nurse Rostering web site at http://www.asap.cs.nott.ac.uk/projects/nmhpr/data

& planning

Nurse Rostering Problems

- Problem formulation
  - Hard constraints
    - binding, feasibility, or imperative planning rules
  - Soft constraints
    - floppy, non binding, preference planning rules
  - Weights
    - to specify relative priorities
    - weighted sum objective function

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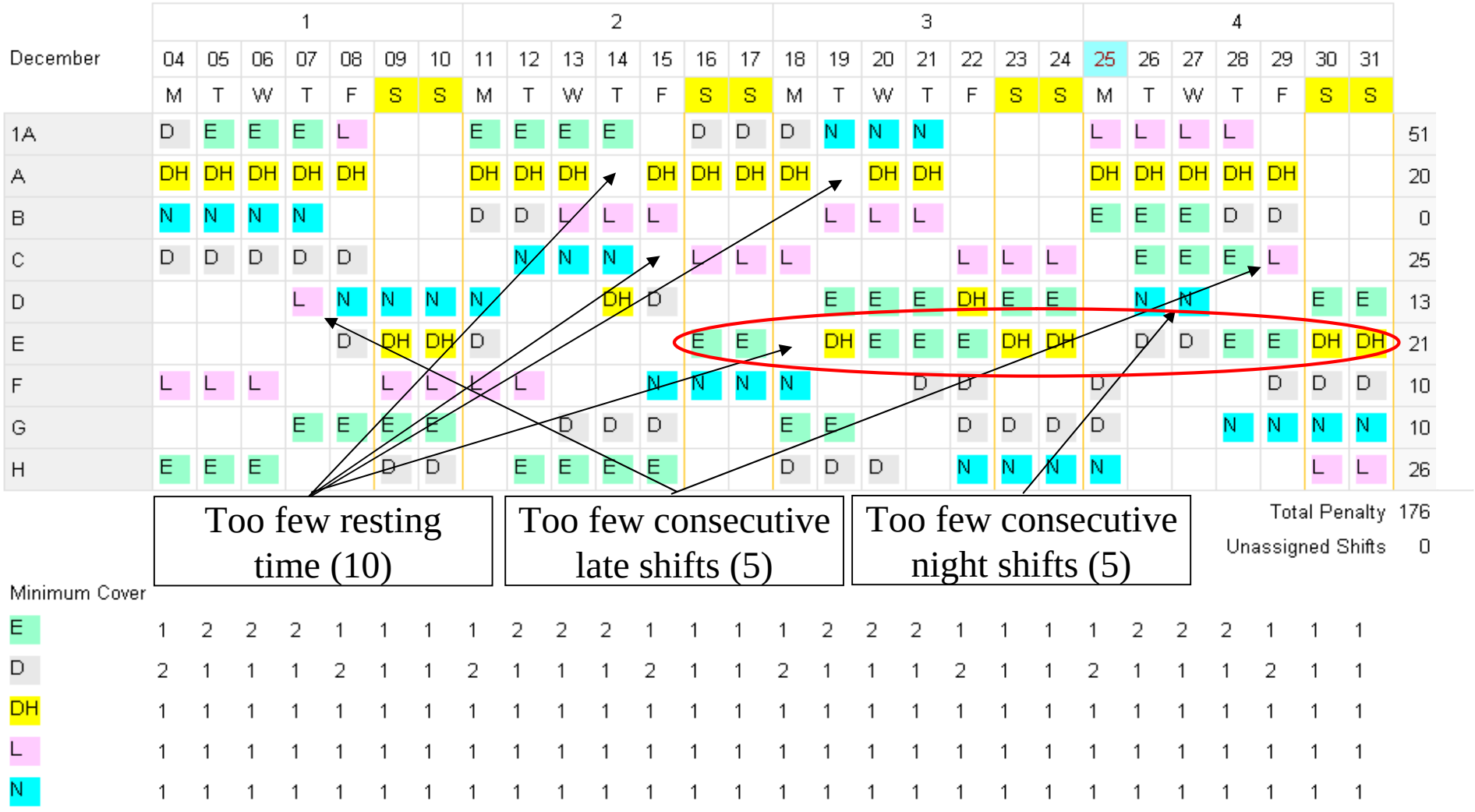
Nurse Rostering Problems



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Nurse Rostering web site at http://www.asap.cs.nott.ac.uk/projects/nmhpr/data

& planning

Nurse Rostering Research

- Meta-heuristics heavily used in nurse rostering[BUR04]
  - GAs[AIC04,07], Memetic Algorithm[VAN01,OZC07], Tabu Search[DOW98], Variable Neighbourhood Search [BUR07], etc
- Hyper-heuristics showed to be flexible and effective
  - TS Hyper-heuristic[BUR03], Rule-Based Hyper-heursitic[AIC07a], MA hyper-heuristics[OZC07a]

Nurse Rostering Research

- Mathematical programming also report good results
  - Hybridised with meta-heuristics[BUR07]
- Others
  - Case based reasoning[BED06]
  - Multi-objective[BUR07a]

Nurse Rostering Research

- Heuristics
  - Advantages
    - Can exploit problem specific information
    - Do not require expensive software packages
  - Disadvantages
    - More programming involved
    - Can be inconsistent

Nurse Rostering Benchmarks

- Very few benchmark nurse rostering problems
  - No typical nurse rostering problem
  - Each hospital has its own problem with a variety of complicated objective functions and lots of constraints
- Benchmarks would help validate algorithms
  - We are collecting real-world problems at http://www.asap.cs.nott.ac.uk/projects/nmhpr/data
  - Encourage collaboration and competition

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Computer Science & Information Technology

Faculty of Science

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Personnel Scheduling Data Sets and Benchmarks

[data] [software] [documentation] [changes] [contact]

Overview

Personnel scheduling problems and benchmarks. These are test instances for the problem of automated personnel schedulir Most of the benchmark problems provided here are nurse rostering problems and based on real world data. See t documentation section for more information on the format of the data and software provided for using the data sets and t development of new solvers.

Data sets

		Best known solutions	
File	GPost.xml	7	html xml
Problem	GPost	8	html xml
Comments	This is a small problem and a nice introductory example.		
Employees	8		
Schedule length	4 weeks		
Cover type	Cover is specified per shift, over and under coverage is not allowed.		
Other versions	GPost-B.xml Same as GPost.xml but without the requests on the first two days.	5	html xml

Nurse Rostering Benchmarks

- Collected from real hospitals firstly by KaHo Sint-Lieven, Belgium
  - Anonymized, removed with confidential information and country specific constraints
- Updated frequently by ASAP Group
  - More recent data from UK, The Netherlands and Canada

Nurse Rostering Benchmarks

- XML
  - flexible, extendible
  - simple representation of different problems
- API evaluation function
  - Standard measure for scientific comparisons

Personnel Rostering Variants

- Staffing Problem
  - Determine the optimal workforce size
  - Factors to consider
    - Available budget
    - Nurse to patient ratios
    - Predicted sick and annual leave
    - Cost and availability of agency nurses
  - Workforce scheduling occurs less frequently

Personnel Rostering Variants

- Cyclic Scheduling
  - All nurses repeatedly work the same pattern
  - Generate one pattern and assign it to all nurses offsetting it each time
  - Advantages
    - Everyone works the same schedule
    - Nurses know schedules a long time in advance
  - Disadvantages
    - Does not easily handle fluctuations in cover requirements
    - Less flexible in satisfying personal requests

Personnel Rostering Variants

- Non-Cyclic Scheduling
  - Each nurse receives a different work pattern
  - Advantages
    - Satisfies personal requests
    - Handles day to day variations in cover requirements
  - Disadvantages
    - Need to be created every planning period
    - More complicated models

Content

- Nurse rostering problems
  - …
- Recent Approaches in ASAP
  - A decomposition approach
  - A sequence based construction approach
  - A hybrid variable neighbourhood search
  - Other related work

A Decomposition Approach

- The problem
  - To create monthly schedules for wards
  - Different types of nurses (PT, FT)
  - 4 shift types and demand in a week
  - Derived from real-world problems in ORTEC, Netherlands

A Decomposition Approach

- The problem

12 Full-time nurses	36 hours/week
1 Part-time nurse	32 hours/week
3 Part-time nurses	20 hours/week

			Demand						
Shift type	Start time	End time	Mon	Tue	Wed	Thu	Fri	Sat	Sun
Early	07:00	16:00	3	3	3	3	3	2	2
Day	08:00	17:00	3	3	3	3	3	2	2
Late	14:00	23:00	3	3	3	3	3	2	2
Night	23:00	07:00	1	1	1	1	1	1	1

A Decomposition Approach

- Hard constraints
  - HC1: daily coverage requirement of each shift type
  - HC2: for each day, a nurse works at most one shift
  - HC3: max number of working days per month
  - HC4: max number of on-duty weekends per month
  - HC5: max number of *night* shifts per month
  - HC6: no *night* shift between two non-*night* shifts
  - HC7: min two free days after a series of *night* shifts
  - HC8: max number of consecutive *night* shifts
  - HC9: max number of consecutive working days
  - HC10: no *late* shifts for one particular nurse

A Decomposition Approach

- Soft constraints

SC1	either no shifts or two shifts in weekends	1000
SC2	avoiding a single day between two days off	1000
SC3	length of a series of night shifts	1000
SC4	Min number of free days after a series of shifts	100
SC5	Max/Min number of consecutive assignments of a specific shift type	10
SC6	Max/Min number of weekly working days	10
SC7	Max number of consecutive working days for part-time nurses	10
SC8	avoiding certain shift type successions (e.g. a *day* shift followed by an *early* one, etc)	5

A Decomposition Approach

- The main idea
  - to decompose the problem into cyclic schedules for groups of nurses
  - add workload of remaining nurses
  - in a second step a Variable Neighbourhood Search is applied for further improvement

A Decomposition Approach

	Week 1						
	M	**T**	**W**	**T**	**F**	**S**	**S**
Nurse 1	D	D	D			E	E
Nurse 2	L	L	L				
Nurse 3	E	E	E	L	L		
Nurse 4				E	E	L	L
Nurse 5	N	N			D	D	D

A Decomposition Approach

	Week 1							Week 2						
	M	**T**	**W**	**T**	**F**	**S**	**S**	**M**	**T**	**W**	**T**	**F**	**S**	**S**
Nurse 1	D	D	D			E	E	D	D	D			E	E
Nurse 2	L	L	L					L	L	L				
Nurse 3	E	E	E	L	L			E	E	E	L	L		
Nurse 4				E	E	L	L				E	E	L	L
Nurse 5	N	N			D	D	D	N	N			D	D	D

A Decomposition Approach

	Week 1							Week 2						
	M	**T**	**W**	**T**	**F**	**S**	**S**	**M**	**T**	**W**	**T**	**F**	**S**	**S**
Nurse 1	D	D	D			E	E							
Nurse 2	L	L	L					L	L	L				
Nurse 3	E	E	E	L	L			E	E	E	L	L		
Nurse 4				E	E	L	L				E	E	L	L
Nurse 5	N	N			D	D	D	N	N			D	D	D

D	D	D			E	E

A Decomposition Approach

	Week 1							Week 2						
	M	**T**	**W**	**T**	**F**	**S**	**S**	**M**	**T**	**W**	**T**	**F**	**S**	**S**
Nurse 1	D	D	D			E	E	L	L	L				
Nurse 2	L	L	L					E	E	E	L	L		
Nurse 3	E	E	E	L	L						E	E	L	L
Nurse 4				E	E	L	L	N	N			D	D	D
Nurse 5	N	N			D	D	D							

D	D	D			E	E

A Decomposition Approach

	Week 1							Week 2						
	M	**T**	**W**	**T**	**F**	**S**	**S**	**M**	**T**	**W**	**T**	**F**	**S**	**S**
Nurse 1	D	D	D			E	E	L	L	L				
Nurse 2	L	L	L					E	E	E	L	L		
Nurse 3	E	E	E	L	L						E	E	L	L
Nurse 4				E	E	L	L	N	N			D	D	D
Nurse 5	N	N			D	D	D	D	D	D			E	E

...

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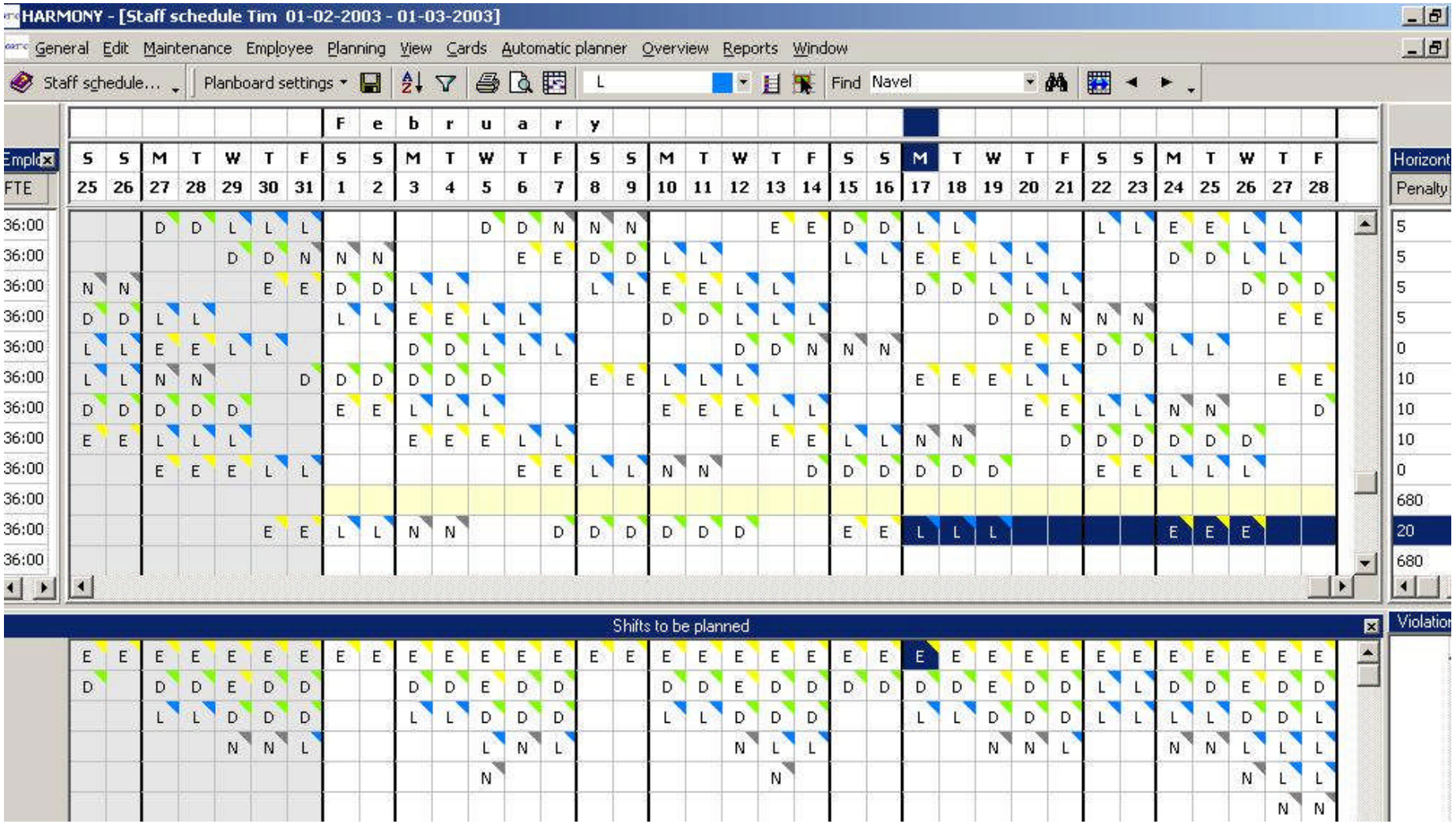
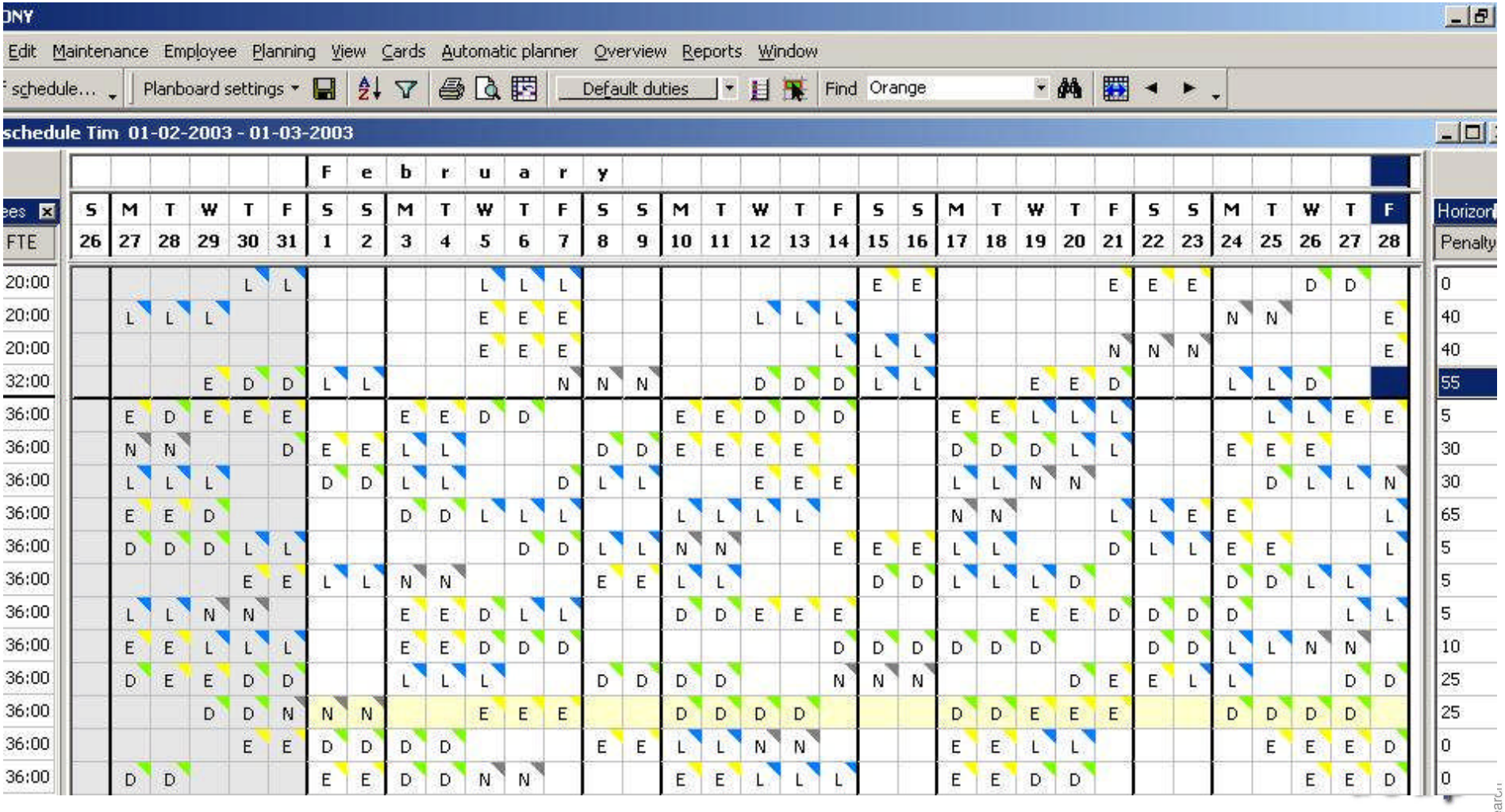
A Decomposition Approach



Recent Research on Nurse Rostering in ASAP

A Decomposition Approach



A Decomposition Approach

- Hybrid GA
  - 630 (5 min) → 505 (40 min) → 411 (6 hours)
- Hybrid VNS
  - 466 (1 min)

- Decomposition + construction
  - 340
- VNS after Decomposition + construction
  - 170 (< 1 min)

Content

- Nurse rostering problems
  - …
- Recent Approaches in ASAP
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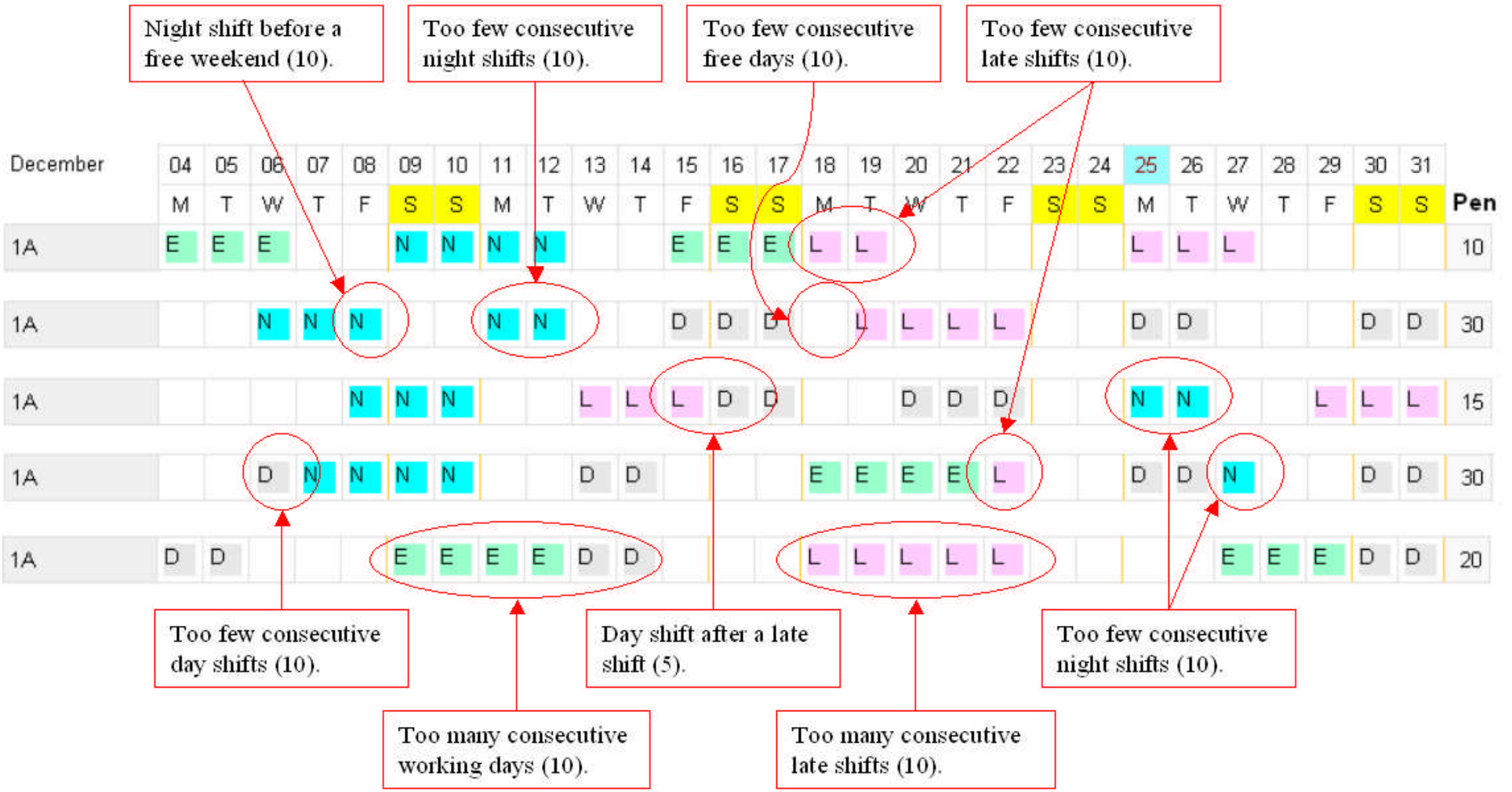
  - A sequence based construction approach
  - A hybrid variable neighbourhood search
  - Other related work

Recent Research on Nurse Rostering in ASAP

Sequence Based Adaptive Approach



Sequence Based Adaptive Approach

- Problems derived from real-world
  - Large number of constraints of different types, and different importance
  - Time consuming when searching for good rosters

	Hard Constraints
1	Shifts which require certain skills can only be taken by (or assigned to) nurses who have those skills
2	The shift coverage requirements must be fulfilled

Sequence Based Adaptive Approach

	Soft Constraint
1	Minimum rest time between shifts
2	Alternative skill (if a nurse is able to cover a shift but prefers not to as it does not require his/her primary skill)
3	Maximum number of shift assignments
4	Maximum number of consecutive working days
5	Minimum number of consecutive working days
6	Maximum number of consecutive non-working days
7	Minimum number of consecutive non-working days
8	Maximum number of hours worked
9	Minimum number of hours worked

Sequence Based Adaptive Approach

	Soft Constraint
10	Maximum total number of assignments for all Mondays, Tuesdays, Wednesdays, etc
11	Maximum number of a certain shift type worked (e.g. maximum seven night shifts for the planning period)
12	Maximum number of a certain shift type worked per week (same as above but for each individual week)
13	Valid number of consecutive shifts of the same type
14	Free days after night shifts
15	Complete weekends (i.e. shifts on both Saturday and Sunday, or no shift over the weekend)
16	No night shifts before free weekends

Sequence Based Adaptive Approach

	Soft Constraint
17	Identical shift types during the weekend
18	Maximum number of consecutive working weekends
19	Maximum number of working weekends in four weeks
20	Maximum number of working bank holidays
21	Shift type successions (e.g. Is shift type A allowed to follow B the next day, etc)
22	Requested days on or off
23	Requested shifts on or off
24	Tutorship (employee X present when employee Y is working)
25	Working separately (employee X not present when employee Y is working)

Sequence Based Adaptive Approach

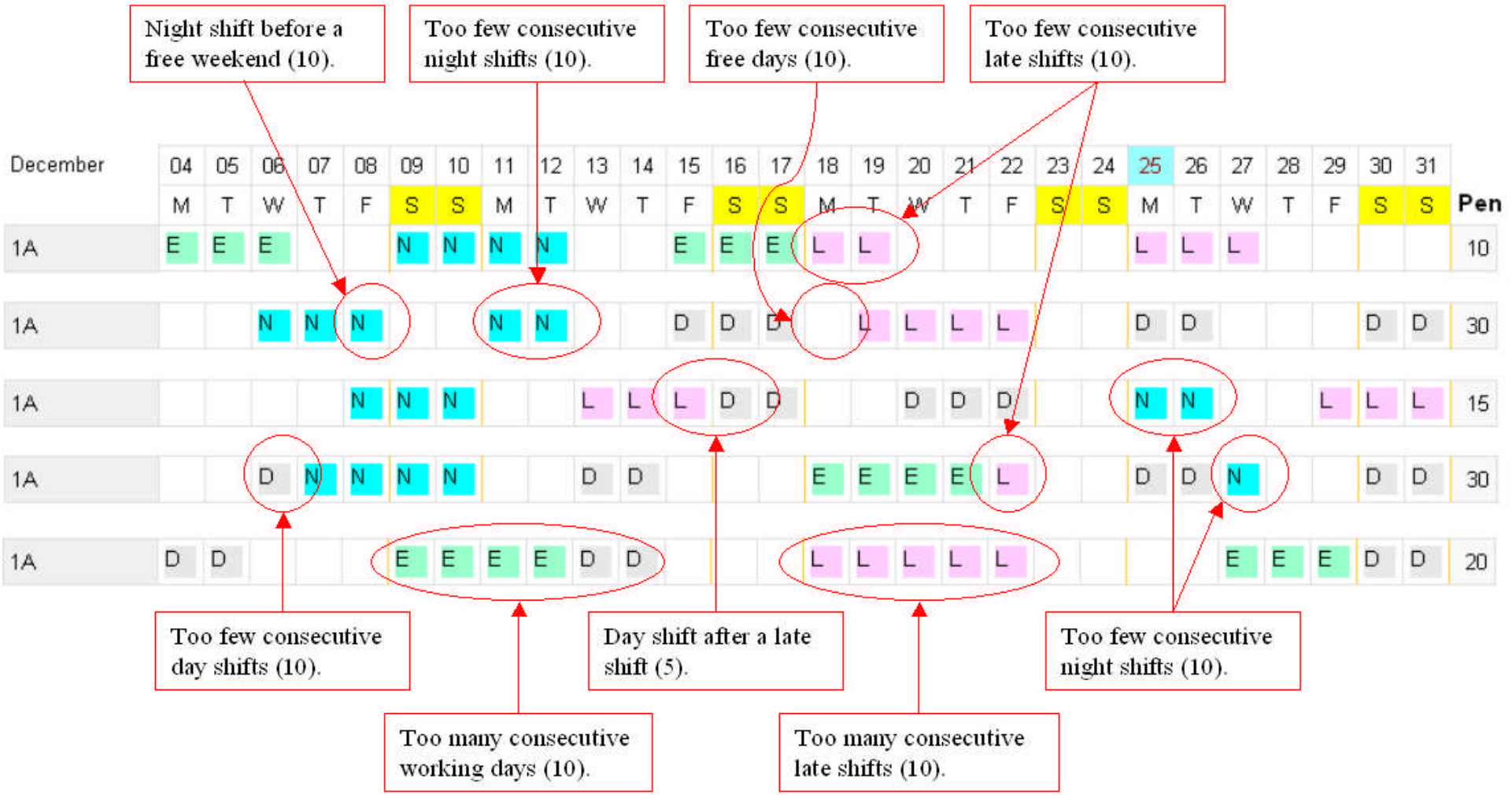
- In literature:
  - Constraints are usually grouped as *hard* and *soft* constraints in most work
  - A few work consider feasible patterns (or work-stretch) of one week, or two weeks, associated with pre-assigned costs

Sequence Based Adaptive Approach

- In our work:
  - Problems are firstly modelled by categorising constraints into 3 types, *Sequence*, *Schedule* and *Roster* related
  - Penalties of *sequences*, *schedules* and *roster* are calculated by corresponding constraints

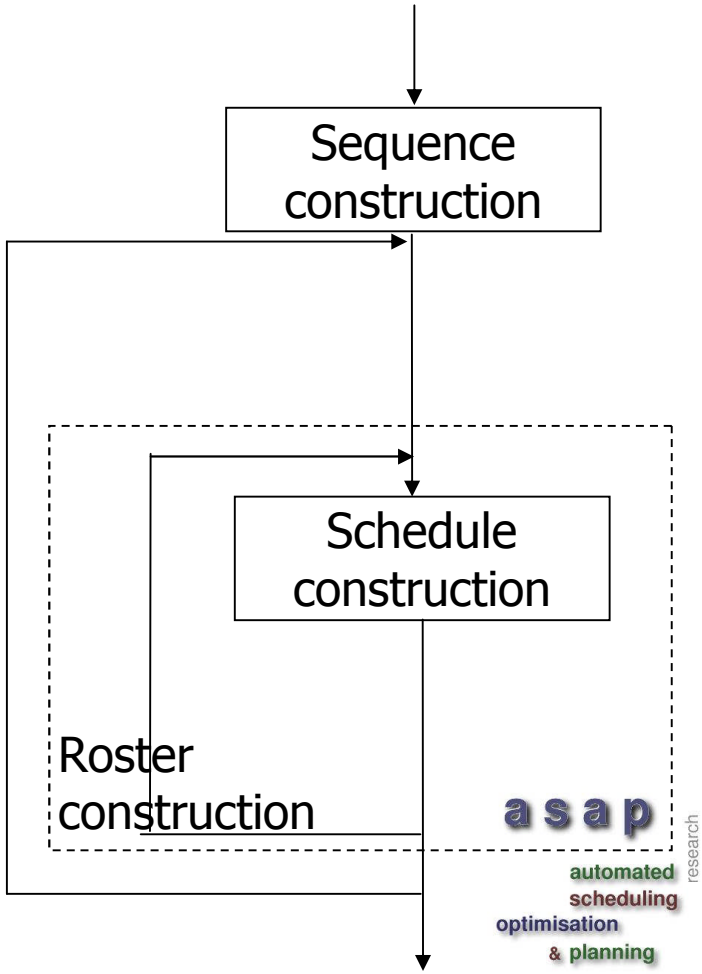
Sequences	A series of shifts for nurses i.e. EEELL
Schedules	Ordered list of sequences and days off
Roster	Overall solution consisting of same length schedules of the scheduling period

Sequence Based Adaptive Approach



Sequence Based Adaptive Approach

- In our work:
  - Two stage approach
    - Construct high quality sequences for each nurse considering only *sequence* related constraints
    - Construct schedules and roster considering only *schedule* and *roster* related constraints



Sequence Based Adaptive Approach

	Hard Constraints	Type
1	Shifts which require certain skills can only be taken by (or assigned to) nurses who have those skills	sequence
2	The shift coverage requirements must be fulfilled	roster

	Soft Constraints	Type
1	Minimum rest time between shifts	sequence
2	Alternative skill (if a nurse is able to cover a shift but prefers not to as it does not require his/her primary skill)	sequence
3	Maximum number of shift assignments	schedule
4	Maximum number of consecutive working days	sequence
5	Minimum number of consecutive working days	sequence
...	...	...

Sequence Based Adaptive Approach

- Decomposition on complex problems
  - Our previous work decompose the problem by considering sub-groups of nurses
  - This work decompose the problem in a different way
    - Constraints are dealt with in different stages
  - Overall aim is to reduce the complexity of the problem and size of the search space

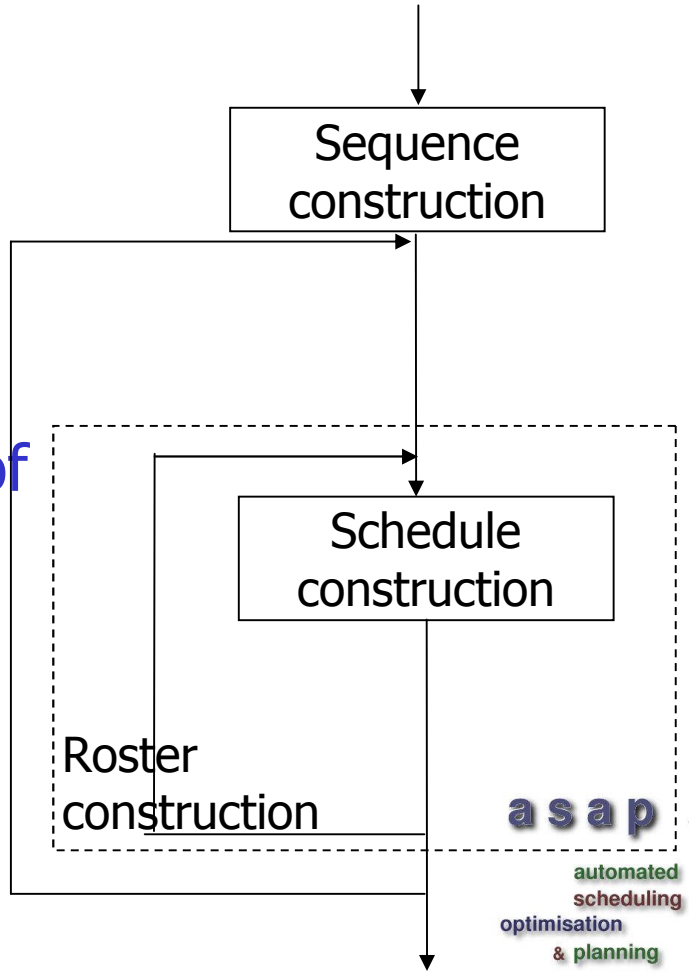
Sequence Based Adaptive Approach

- Stage I: sequence construction for each nurse
  - Construct sequences by considering
    - *sequence* related hard constraints
    - *sequence* related soft constraints
    - length of up to 5
  - Best 50 are ranked

Shift Sequences	Penalty	Comment
E, E, E	0	
D, D, E, E, E	5	E not preferred to follow D.
L, L, L, D, D	5	D not allo preferred wed to follow L.
N, N	10	Two N's not preferred.
E, D, D	10	One E not preferred.

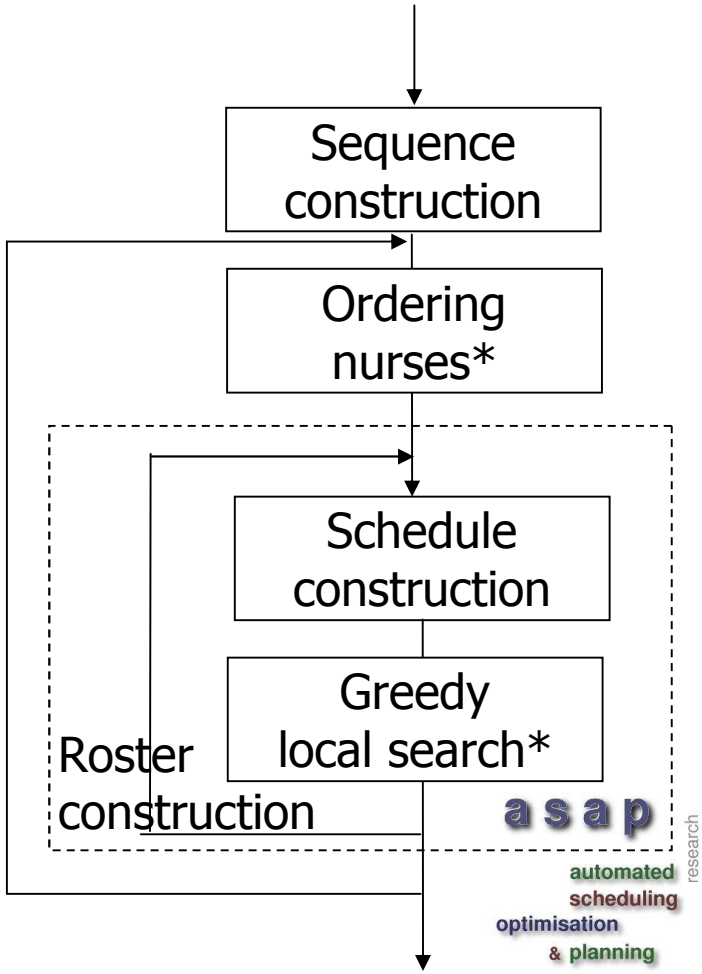
Sequence Based Adaptive Approach

- Stage II: schedule and roster construction
  - Build schedules based on sequences for each nurse considering only *schedule* related constraints
  - Iteratively combine schedules of nurses to construct rosters considering only *roster* related constraints



Sequence Based Adaptive Approach

- Stage II: schedule and roster construction
  - Hybridisations of different techniques are possible with this simple and fast approach
    - Greedy local search: improvement during and after roster construction
    - Adaptive ordering: nurses with worse schedules are scheduled first in the next iteration



Sequence Based Adaptive Approach

- Experiment results
  - Without adaptive ordering
    - Greedy local search does not make much improvement
  - With adaptive ordering
    - Improvement by greedy local search around 4%

Sequence Based Adaptive Approach

- Conclusions
  - Problem formulation to decompose the constraints of different types → smaller search space
  - Simple and fast technique, usually take a few seconds to 2 minutes for problems up to 46 nurses and more than four weeks
  - Easily hybridised with other techniques for further improvement

Content

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  - A decomposition approach
  - A sequence based construction approach
  - A hybrid variable neighbourhood search
  - Other related work

Hybrid Variable Neighbourhood Search

- Meta-heuristics are the state-of-the-art in nurse rostering research[BUR04]
  - Most algorithms use only one neighbourhood operator
- Variable neighbourhood search (VNS) showed to be very effective on a number of scheduling problems
  - Employ at least two neighbourhood operators
  - Effective on escaping from local optimum

Hybrid Variable Neighbourhood Search

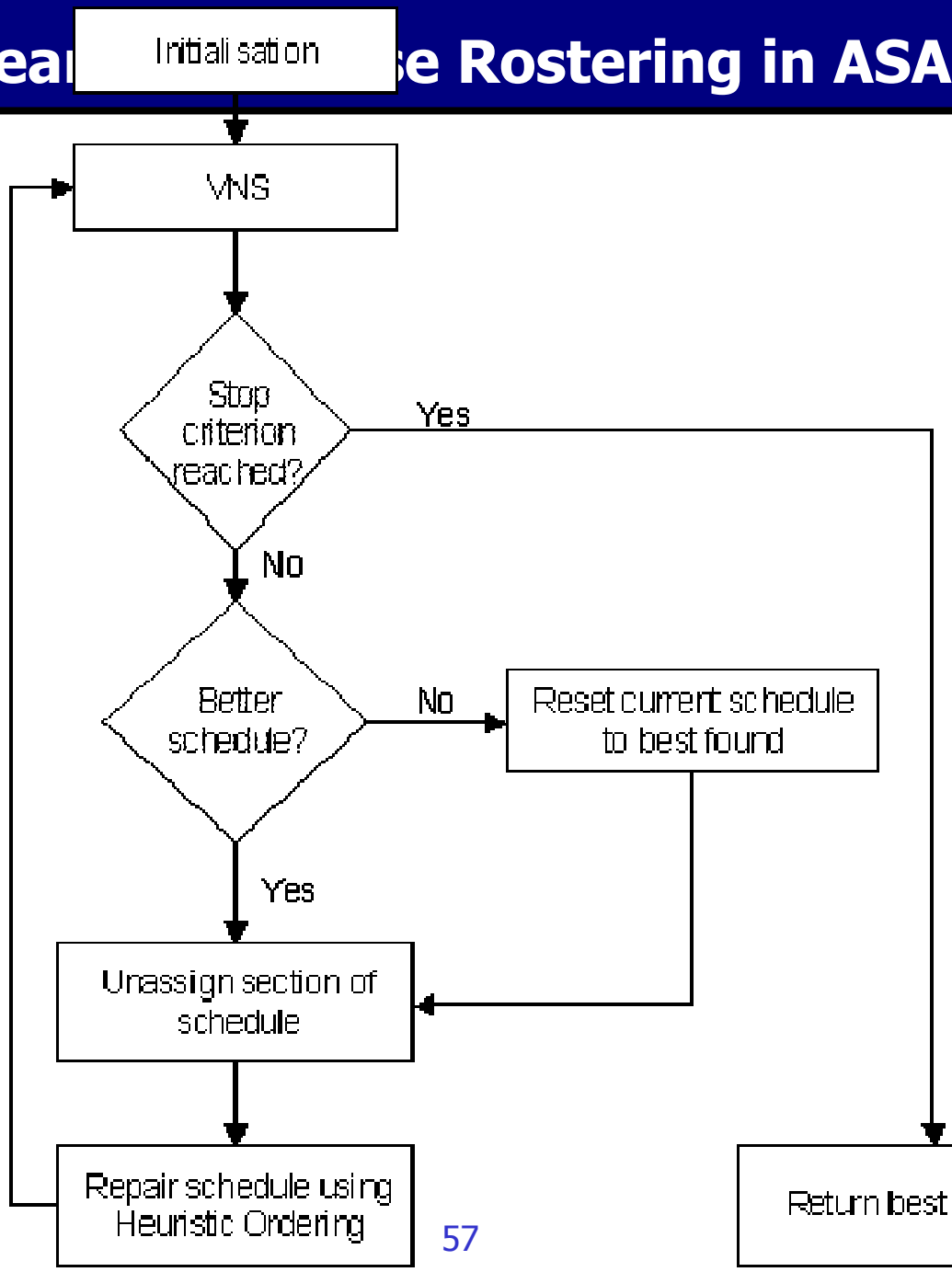
- HARMONY™
  - Automated workforce management software
  - Developed by ORTEC, The Netherlands, an international consultancy company on planning, scheduling, optimisation and decision support

- This work improved the algorithm in HARMONY™

Hybrid Variable Neighbourhood Search

- In this work
  - Heuristic ordering
    - to order shifts for construction
  - Repairing method
    - remove worse part of roster and re-construct
  - VNS
    - improvement upon rosters

Recent Resea[illegible]e Rostering in ASAP



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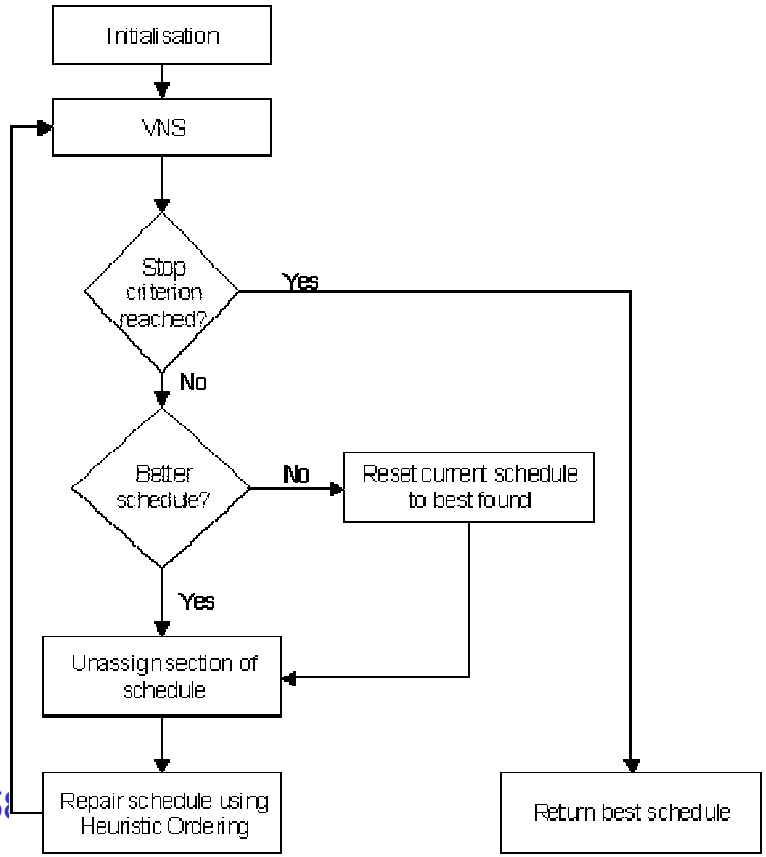
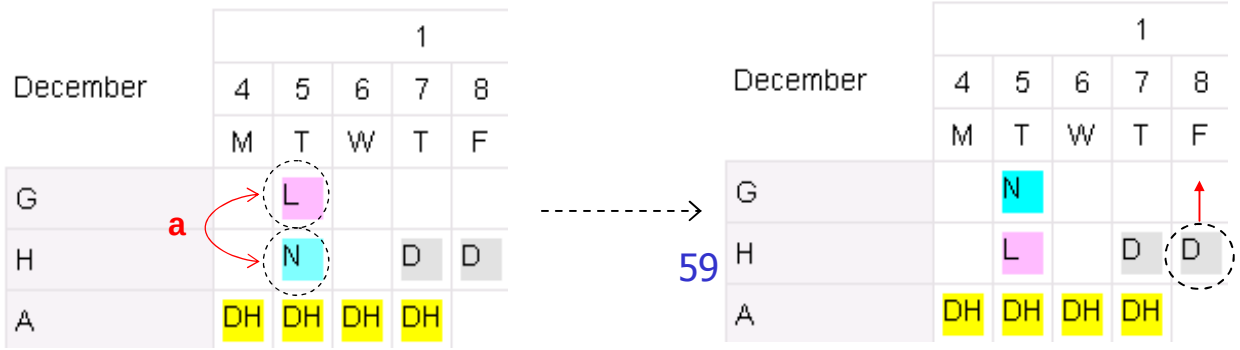
Hybrid Variable Neighbourhood Search

- Heuristic ordering
  - Order shifts for construction in initialisation and repair
  - More ***troublesome*** shifts assigned first
  - Criteria to evaluate the shifts
    - Type of shifts, number of employees able to cover it, etc



Hybrid Variable Neighbourhood Search

- Variable Neighbourhood Search
  - Neighbours of a solution
    - those schedules that can be obtained by making a "move" e.g. single shifts swapped between any two nurses
  - Two neighbourhood operators
    - Assign a shift to another nurse
    - Swap shifts between nurses



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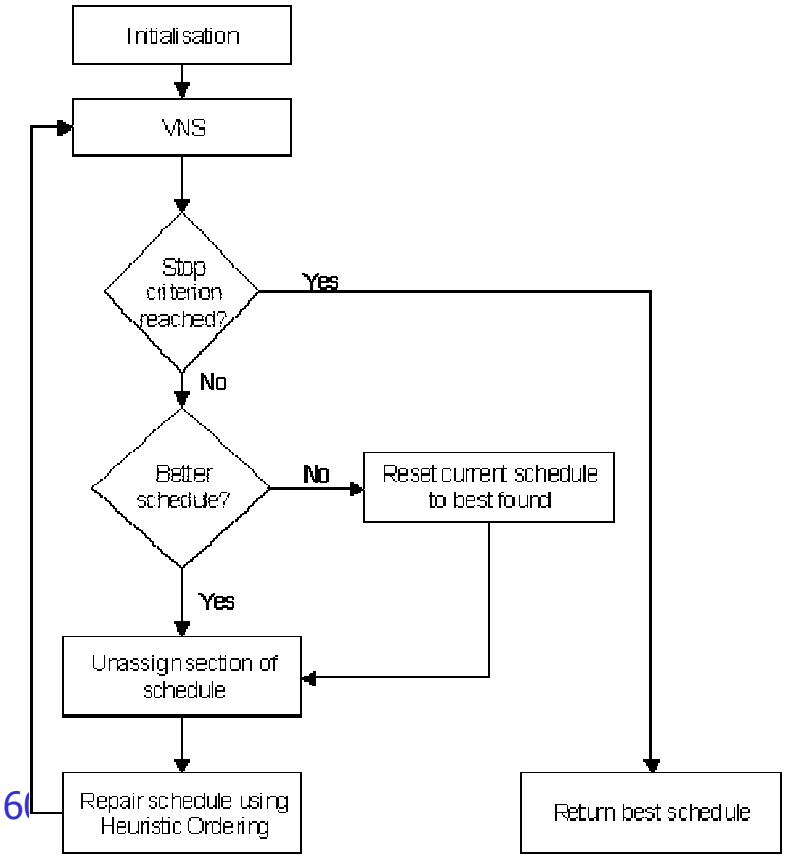
asap automated scheduling optimisation & planning research

Hybrid Variable Neighbourhood Search

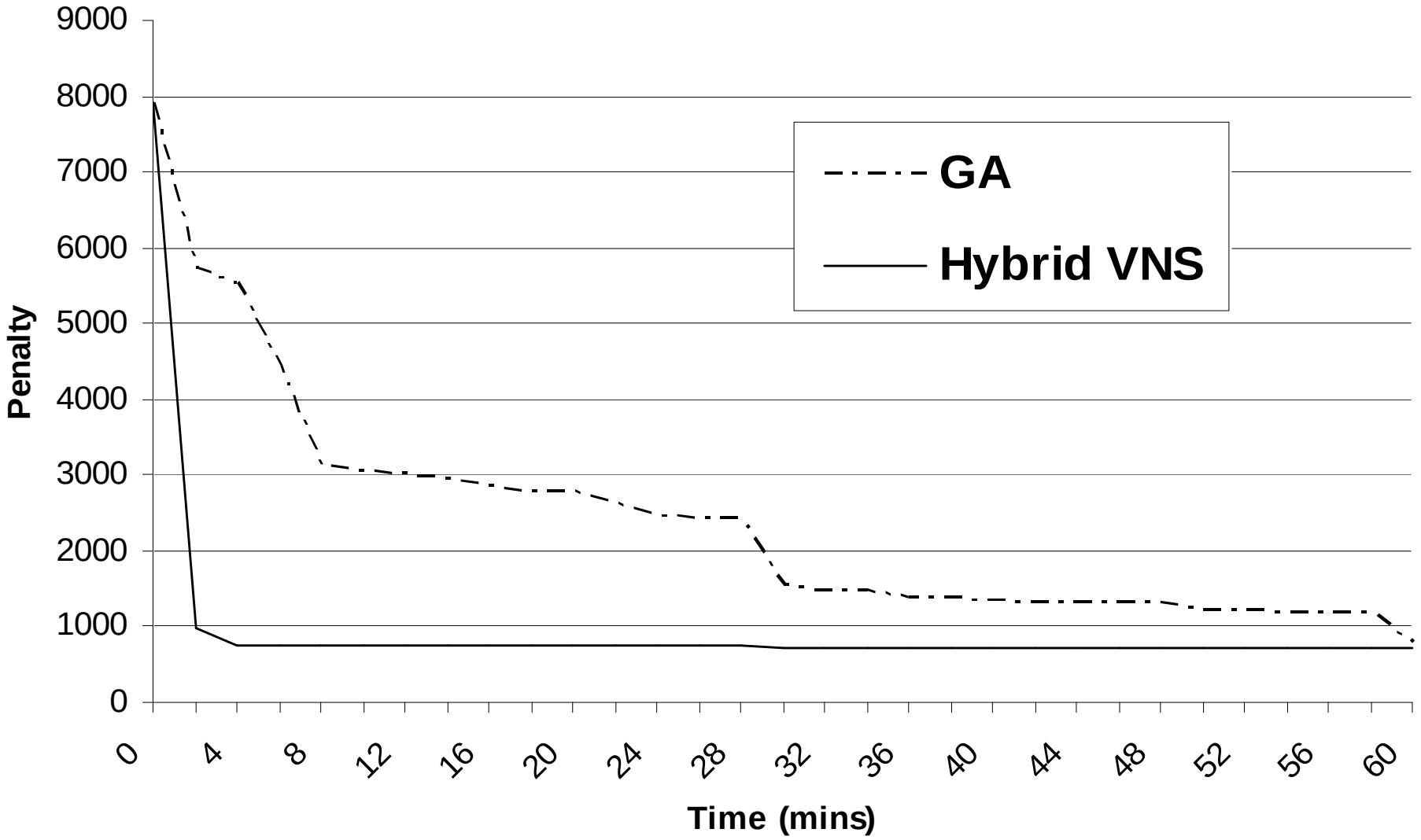
- Repairing method
  - After VNS reached to a local optimum
  - Un-assign a section of roster for further possible improvement operators
  - Re-assign shifts ordered by heuristic ordering



Hybrid Variable Neighbourhood Search

	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
GA (60 mins)	775	**1791**	2030	612	2296	9466	781	**4850**	**615**	736	2126	625
VNS (30 mins)	735	1950	2055	501	2285	9312	660	4975	761	665	2041	625
VNS (60 mins)	**735**	1866	**2010**	**457**	**2161**	**9291**	**481**	4880	647	**665**	**2030**	**520**

Hybrid Variable Neighbourhood Search



Hybrid Variable Neighbourhood Search

Algorithm	Penalty
Hybrid VNS after 30 minutes	736
Hybrid VNS after 60 minutes	706
Best ever G.A. (24 hours)	681
Previous best known (made by manual improvements)	587
Hybrid VNS after 12 hours	541

Hybrid Variable Neighbourhood Search

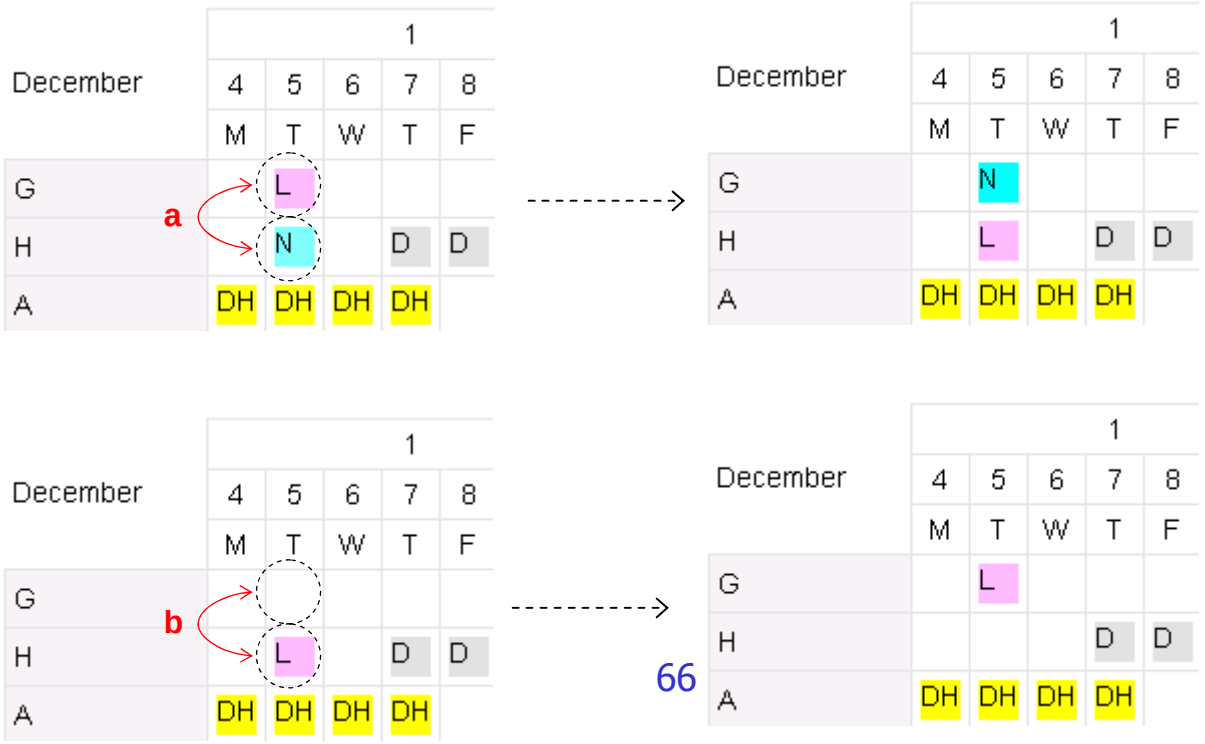
- Conclusions
  - Relatively straightforward and highly effective
  - Superior to the existing algorithm in a commercial software

Content

- Nurse rostering problems
  - …
- Recent approaches in ASAP
  - A decomposition approach
  - A sequence based construction approach
  - A hybrid variable neighbourhood search
  - Other ongoing work

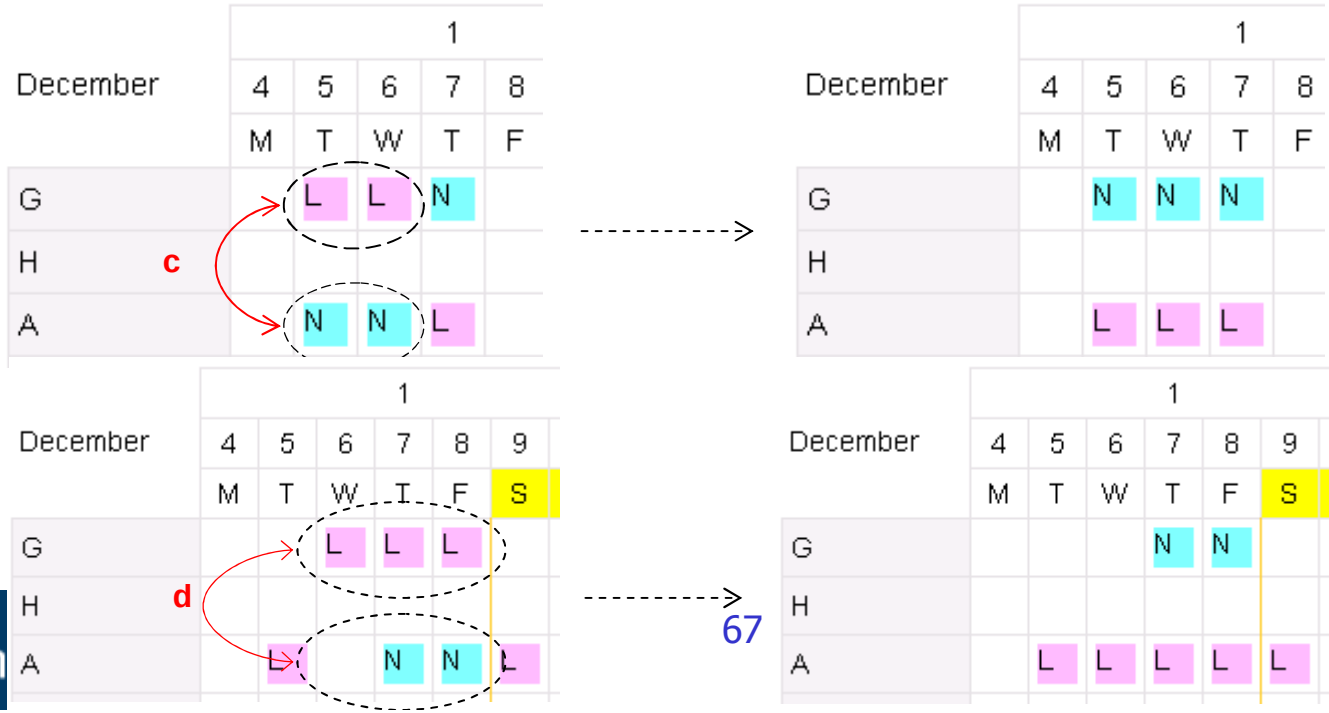
Variable Depth Search

- Basic VNS
  - Move single shift to another nurse
  - Swap two shifts between nurses



Variable Depth Search

- Extend basic VNS
  - include neighbour solutions which differ by an exchange of a **block** of shifts between two nurses



Variable Depth Search

- Form chains of moves/swaps
- Each neighbour in the neighbourhood for the best solution found so far is a possible starting point for the chain of moves
- The second nurse in the last move is the first nurse in the next move

Variable Depth Search

- If at any point a new best solution is found, set it as the current solution and look for another set of moves
- If the chain cannot be continued, we go back to the current best solution, take an untried starting move and try to form a chain it
- Algorithm terminates when no untried starting points in the current best solution

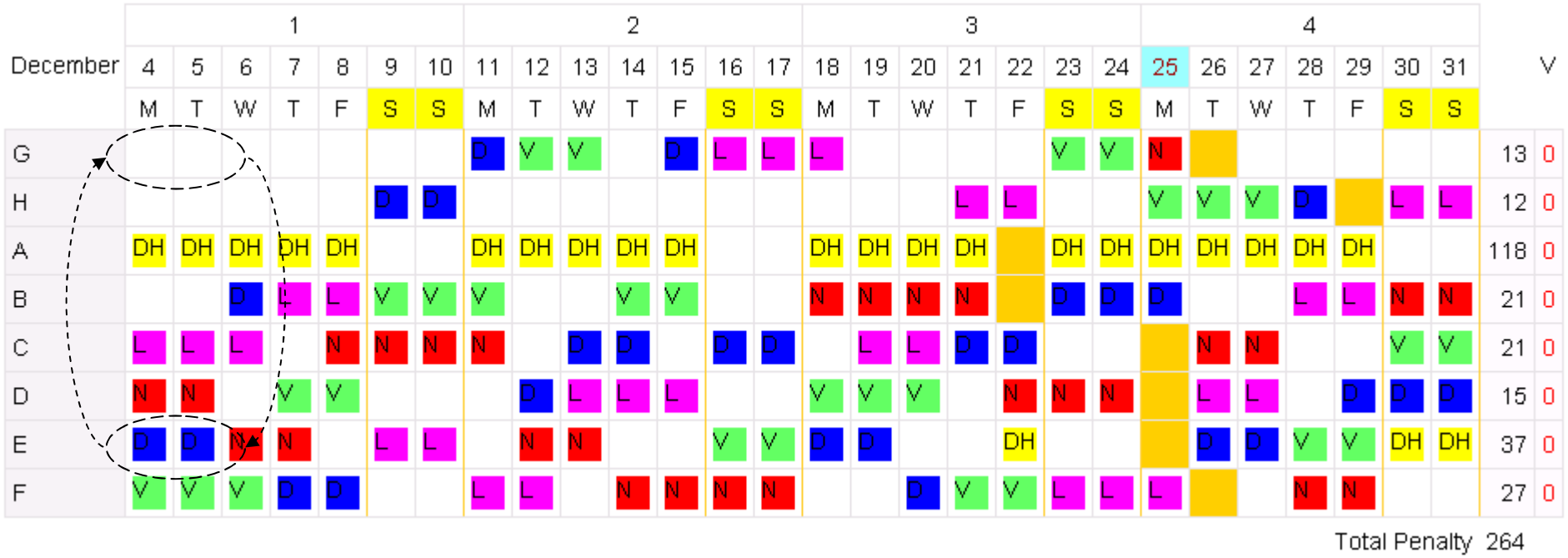
Recent Research on Nurse Rostering in ASAP

	1							2							3							4								
December	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30	31		V
	M	T	W	T	F	S	S	M	T	W	T	F	S	S	M	T	W	T	F	S	S	M	T	W	T	F	S	S		
G								D	V	V		D	L	L	L					V	V	N							13	0
H						D	D											L	L			V	V	V	D		L	L	12	0
A	DH	DH	DH	DH	DH			DH	DH	DH	DH	DH			DH	DH	DH	DH		DH	DH	DH	DH	DH	DH	DH			118	0
B			D	L	L	V	V	V			V	V			N	N	N	N		D	D	D			L	L	N	N	21	0
C	L	L	L		N	N	N	N		D	D		D	D		L	L	D	D				N	N			V	V	21	0
D	N	N		V	V				D	L	L	L			V	V	V		N	N	N		L	L		D	D	D	15	0
E	D	D	N	N		L	L		N	N			V	V	D	D			DH				D	D	V	V	DH	DH	37	0
F	V	V	V	D	D			L	L		N	N	N	N			D	V	V	L	L	L			N	N			27	0

Total Penalty 264

(Total penalty = 264)

Recent Research on Nurse Rostering in ASAP



	1							2							3							4							V	
December	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30	31		
	M	T	W	T	F	S	S	M	T	W	T	F	S	S	M	T	W	T	F	S	S	M	T	W	T	F	S	S		
G								D	V	V		D	L	L	L					V	V	N							13	0
H						D	D											L	L			V	V	V	D		L	L	12	0
A	DH	DH	DH	DH	DH			DH	DH	DH	DH	DH			DH	DH	DH	DH		DH	DH	DH	DH	DH	DH	DH			118	0
B			D	L	L	V	V	V			V	V			N	N	N	N		D	D	D			L	L	N	N	21	0
C	L	L	L		N	N	N	N		D	D		D	D		L	L	D	D				N	N			V	V	21	0
D	N	N		V	V				D	L	L	L			V	V	V		N	N	N		L	L		D	D	D	15	0
E	D	D	N	N		L	L		N	N			V	V	D	D			DH				D	D	V	V	DH	DH	37	0
F	V	V	V	D	D			L	L		N	N	N	N			D	V	V	L	L	L			N	N			27	0

Total Penalty 264

(Total penalty = 264)

Recent Research on Nurse Rostering in ASAP

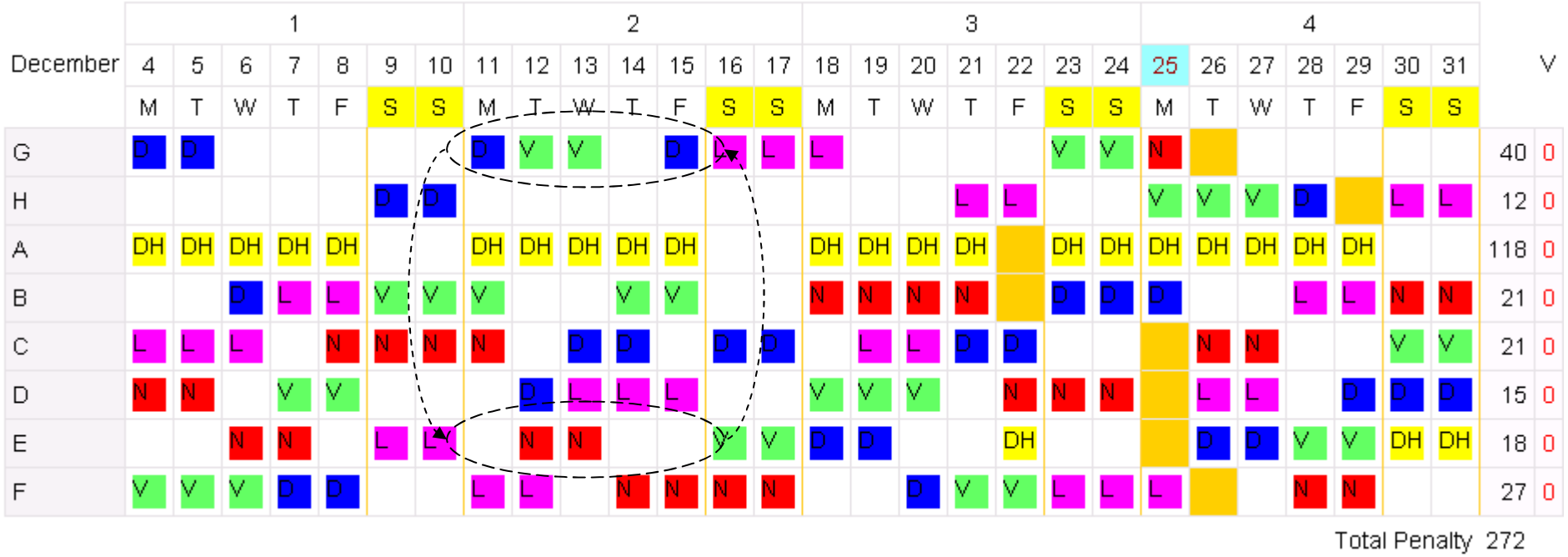
	1							2							3							4								
December	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30	31		V
	M	T	W	T	F	S	S	M	T	W	T	F	S	S	M	T	W	T	F	S	S	M	T	W	T	F	S	S		
G	D	D						D	V	V		D	L	L	L					V	V	N							40	0
H						D	D											L	L			V	V	V	D		L	L	12	0
A	DH	DH	DH	DH	DH			DH	DH	DH	DH	DH			DH	DH	DH	DH		DH	DH	DH	DH	DH	DH	DH			118	0
B			D	L	L	V	V	V			V	V			N	N	N	N		D	D	D			L	L	N	N	21	0
C	L	L	L		N	N	N	N		D	D		D	D		L	L	D	D				N	N			V	V	21	0
D	N	N		V	V				D	L	L	L			V	V	V		N	N	N		L	L		D	D	D	15	0
E			N	N		L	L		N	N			V	V	D	D			DH				D	D	V	V	DH	DH	18	0
F	V	V	V	D	D			L	L		N	N	N	N			D	V	V	L	L	L			N	N			27	0

Total Penalty 272

E's penalty before = 37, now = 18. Change = -19. Pen = 264-19=245
G's penalty before = 13, now = 40. Change = +27. Pen = 245+27=272

(Original penalty = 264)

Recent Research on Nurse Rostering in ASAP



	1							2							3							4								
December	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30	31		V
	M	T	W	T	F	S	S	M	T	W	T	F	S	S	M	T	W	T	F	S	S	M	T	W	T	F	S	S		
G	D	D						D	V	V		D	D	L	L					V	V	N							40	0
H						D	D											L	L			V	V	V	D		L	L	12	0
A	DH	DH	DH	DH	DH			DH	DH	DH	DH	DH			DH	DH	DH	DH		DH	DH	DH	DH	DH	DH	DH			118	0
B			D	L	L	V	V	V			V	V			N	N	N	N		D	D	D			L	L	N	N	21	0
C	L	L	L		N	N	N	N		D	D		D	D		L	L	D	D				N	N			V	V	21	0
D	N	N		V	V				D	L	L	L			V	V	V		N	N	N		L	L		D	D	D	15	0
E			N	N		L	L		N	N			V	V	D	D			DH				D	D	V	V	DH	DH	18	0
F	V	V	V	D	D			L	L		N	N	N	N			D	V	V	L	L	L			N	N			27	0

Total Penalty 272

The University of Nottingham

asap automated scheduling optimisation & planning research

Recent Research on Nurse Rostering in ASAP

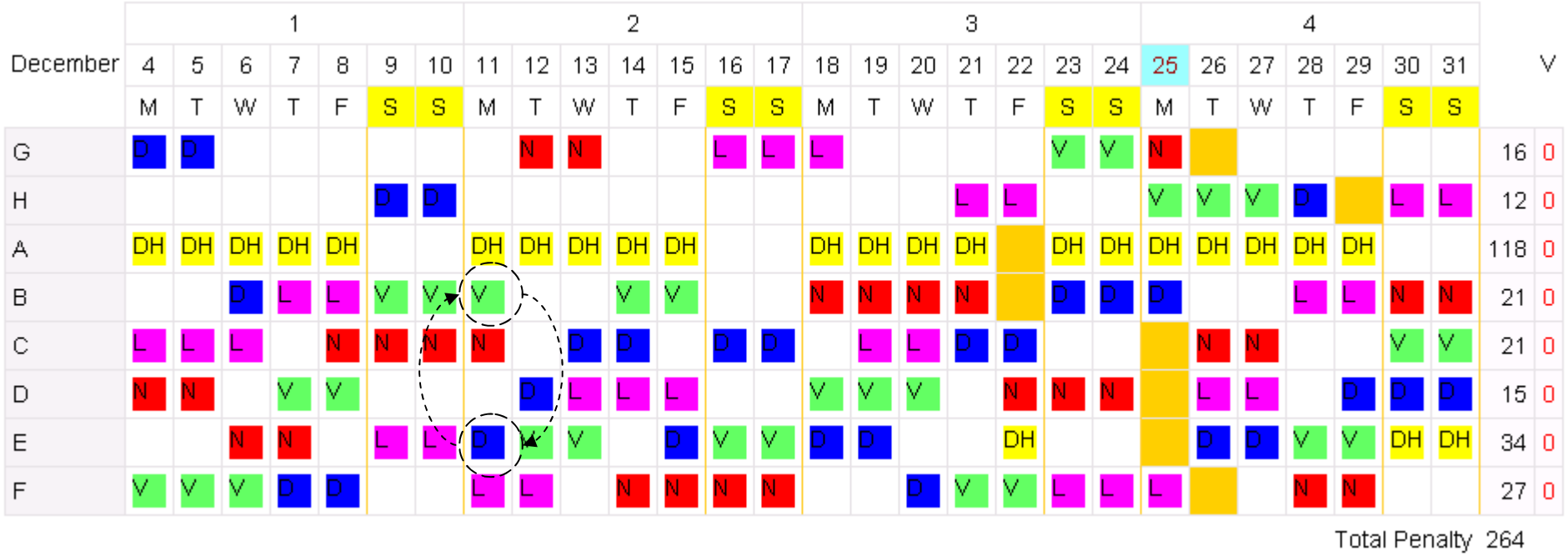
	1							2							3							4								
December	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30	31		V
	M	T	W	T	F	S	S	M	T	W	T	F	S	S	M	T	W	T	F	S	S	M	T	W	T	F	S	S		
G	D	D							N	N			L	L	L					V	V	N							16	0
H						D	D											L	L			V	V	V	D		L	L	12	0
A	DH	DH	DH	DH	DH			DH	DH	DH	DH	DH			DH	DH	DH	DH		DH	DH	DH	DH	DH	DH	DH			118	0
B			D	L	L	V	V	V			V	V			N	N	N	N		D	D	D			L	L	N	N	21	0
C	L	L	L		N	N	N	N		D	D		D	D		L	L	D	D				N	N			V	V	21	0
D	N	N		V	V				D	L	L	L			V	V	V		N	N	N		L	L		D	D	D	15	0
E			N	N		L	L	D	V	V		D	V	V	D	D			DH				D	D	V	V	DH	DH	34	0
F	V	V	V	D	D			L	L		N	N	N	N			D	V	V	L	L	L			N	N			27	0

Total Penalty 264

G's penalty before = 40, now = 16. Change = -24. Pen = 272-24 =248
E's penalty before = 18, now = 34. Change = +16. Pen = 248+16=264

(Original penalty = 264)

Recent Research on Nurse Rostering in ASAP



	1							2							3							4								
December	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30	31		V
	M	T	W	T	F	S	S	M	T	W	T	F	S	S	M	T	W	T	F	S	S	M	T	W	T	F	S	S		
G	D	D							N	N			L	L	L					V	V	N							16	0
H						D	D											L	L			V	V	V	D		L	L	12	0
A	DH	DH	DH	DH	DH			DH	DH	DH	DH	DH			DH	DH	DH	DH		DH	DH	DH	DH	DH	DH	DH			118	0
B			D	L	L	V	V	V			V	V			N	N	N	N		D	D	D			L	L	N	N	21	0
C	L	L	L		N	N	N	N		D	D		D	D		L	L	D	D				N	N			V	V	21	0
D	N	N		V	V				D	L	L	L			V	V	V		N	N	N		L	L		D	D	D	15	0
E			N	N		L	L	D	V	V		D	V	V	D	D			DH				D	D	V	V	DH	DH	34	0
F	V	V	V	D	D			L	L		N	N	N	N			D	V	V	L	L	L			N	N			27	0

Total Penalty 264

Recent Research on Nurse Rostering in ASAP

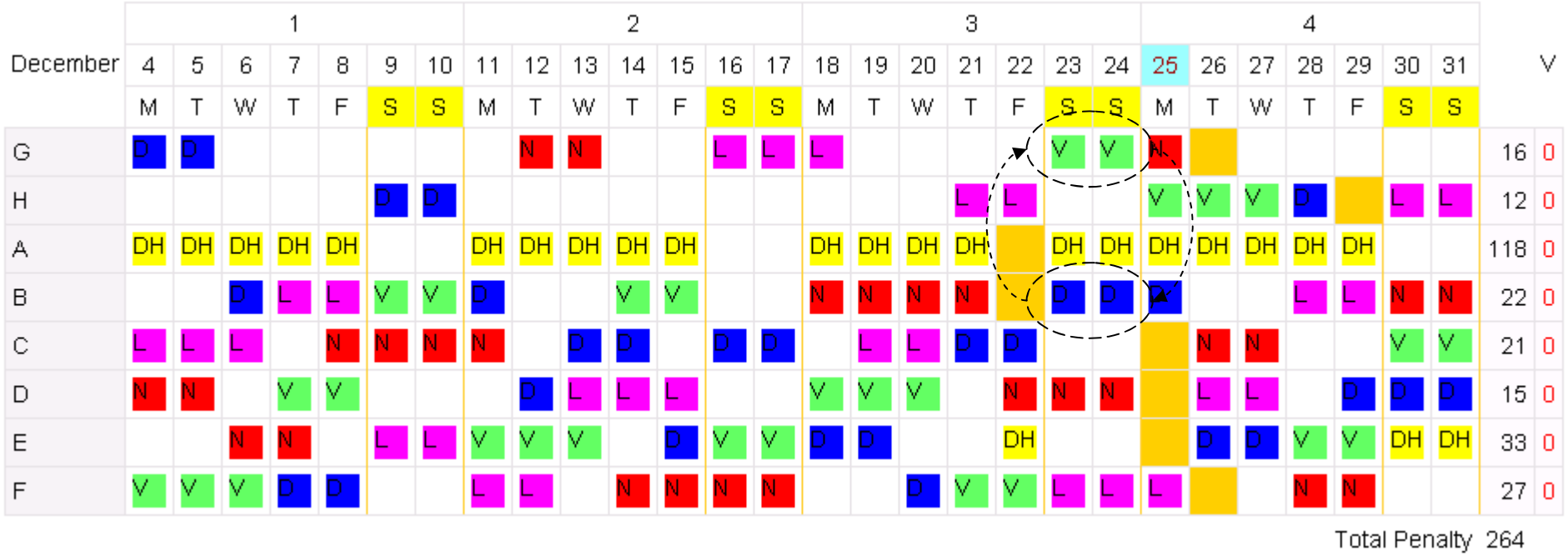
	1							2							3							4								
December	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30	31		V
	M	T	W	T	F	S	S	M	T	W	T	F	S	S	M	T	W	T	F	S	S	M	T	W	T	F	S	S		
G	D	D							N	N			L	L	L					V	V	N							16	0
H						D	D											L	L			V	V	V	D		L	L	12	0
A	DH	DH	DH	DH	DH			DH	DH	DH	DH	DH			DH	DH	DH	DH		DH	DH	DH	DH	DH	DH	DH			118	0
B			D	L	L	V	V	D			V	V			N	N	N	N		D	D	D			L	L	N	N	22	0
C	L	L	L		N	N	N	N		D	D		D	D		L	L	D	D				N	N			V	V	21	0
D	N	N		V	V				D	L	L	L			V	V	V		N	N	N		L	L		D	D	D	15	0
E			N	N		L	L	V	V	V		D	V	V	D	D			DH				D	D	V	V	DH	DH	33	0
F	V	V	V	D	D			L	L		N	N	N	N			D	V	V	L	L	L			N	N			27	0

Total Penalty 264

E's penalty before = 34, now = 33. Change = -1. Pen = 264-1 =263
B's penalty before = 21, now = 22. Change = +1. Pen = 263+1=264

(Original penalty = 264)

Recent Research on Nurse Rostering in ASAP



December	1							2							3							4							V	
	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30	31		
	M	T	W	T	F	S	S	M	T	W	T	F	S	S	M	T	W	T	F	S	S	M	T	W	T	F	S	S		
G	D	D							N	N			L	L	L					V	V	N							16	0
H						D	D											L	L			V	V	V	D		L	L	12	0
A	DH	DH	DH	DH	DH			DH	DH	DH	DH	DH			DH	DH	DH	DH		DH	DH	DH	DH	DH	DH	DH			118	0
B			D	L	L	V	V	D			V	V			N	N	N	N		D	D				L	L	N	N	22	0
C	L	L	L		N	N	N	N		D	D		D	D		L	L	D	D				N	N			V	V	21	0
D	N	N		V	V				D	L	L	L			V	V	V		N	N	N		L	L		D	D	D	15	0
E			N	N		L	L	V	V	V		D	V	V	D	D			DH				D	D	V	V	DH	DH	33	0
F	V	V	V	D	D			L	L		N	N	N	N			D	V	V	L	L	L			N	N			27	0

Total Penalty 264

Recent Research on Nurse Rostering in ASAP

	1							2							3							4								
December	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30	31		V
	M	T	W	T	F	S	S	M	T	W	T	F	S	S	M	T	W	T	F	S	S	M	T	W	T	F	S	S		
G	D	D							N	N			L	L	L							D	D	N						17	0
H						D	D											L	L					V	V	V	D		L	L	12	0
A	DH	DH	DH	DH	DH			DH	DH	DH	DH	DH			DH	DH	DH	DH		DH	DH	DH	DH	DH	DH	DH			118	0
B			D	L	L	V	V	D			V	V			N	N	N	N		V	V	D			L	L	N	N	20	0
C	L	L	L		N	N	N	N		D	D		D	D		L	L	D	D				N	N			V	V	21	0
D	N	N		V	V				D	L	L	L			V	V	V		N	N	N		L	L		D	D	D	15	0
E			N	N		L	L	V	V	V		D	V	V	D	D			DH				D	D	V	V	DH	DH	33	0
F	V	V	V	D	D			L	L		N	N	N	N			D	V	V	L	L	L			N	N			27	0

Total Penalty 263

B's penalty before = 22, now = 20. Change = -2. Pen = 264-2 =262
G's penalty before = 16, now = 17. Change = +1. Pen = 262+1=263

(Original penalty = 264)

Variable Depth Search

- Conclusions
  - More complicated to implement compared with VNS and sequence based constructive method
  - Very effective compared with previous approaches

Rule Based Hyper-heuristics

- Most constructive heuristics use fixed rules
  - A single or combination of rules are used throughout of the schedule construction
  - Schedule quality is usually poor
- A human being can use rules flexibly during solution construction
- How to build schedules by using a set of rules

Rule Based Hyper-heuristics

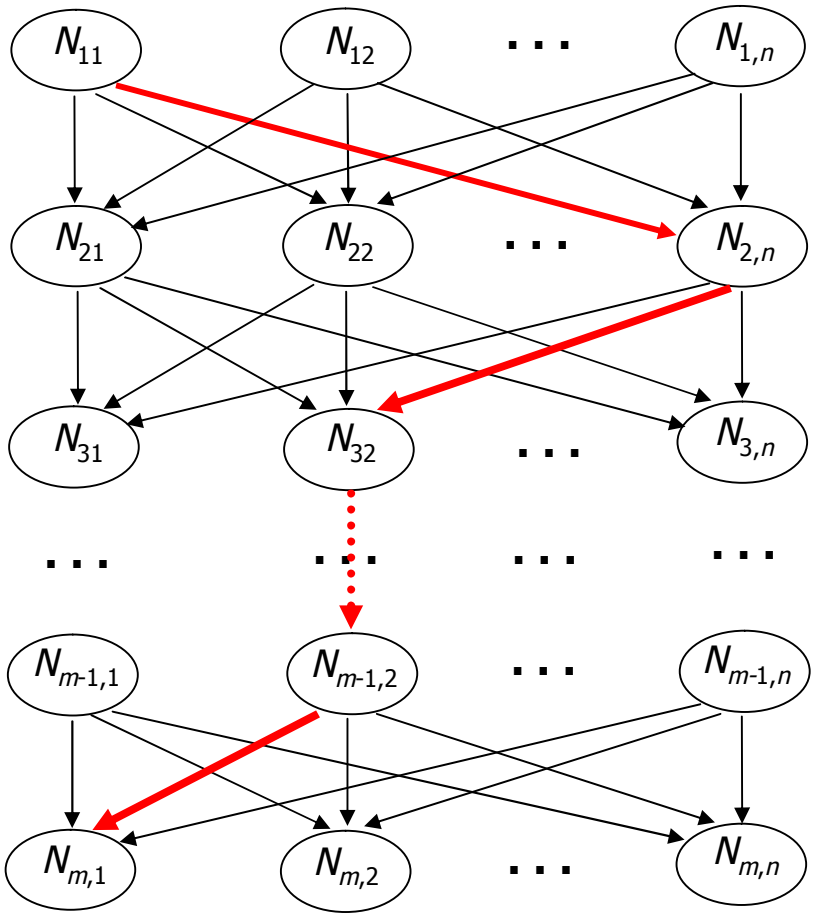
- Produce weekly schedules for wards
- Up to 30 nurses
  - Different grades/skills
- Two shift types: N, D

- Constraints
  - Working contracts
  - Demand for the given number of nurses
  - Higher qualified nurses can substitute less qualified nurses, but not vice versa

Rule Based Hyper-heuristics

- Two stage approach
  - Generate
    - Each shift pattern of one week length is associated with corresponding cost (violation of soft constraints)
    - Pre-processed (411 shift patterns)
  - Allocate
    - Different rules are used to allocate shift patterns to build a schedule
    - Hyper-heuristic is used to search on sequences of rules

Rule Based Hyper-heuristics

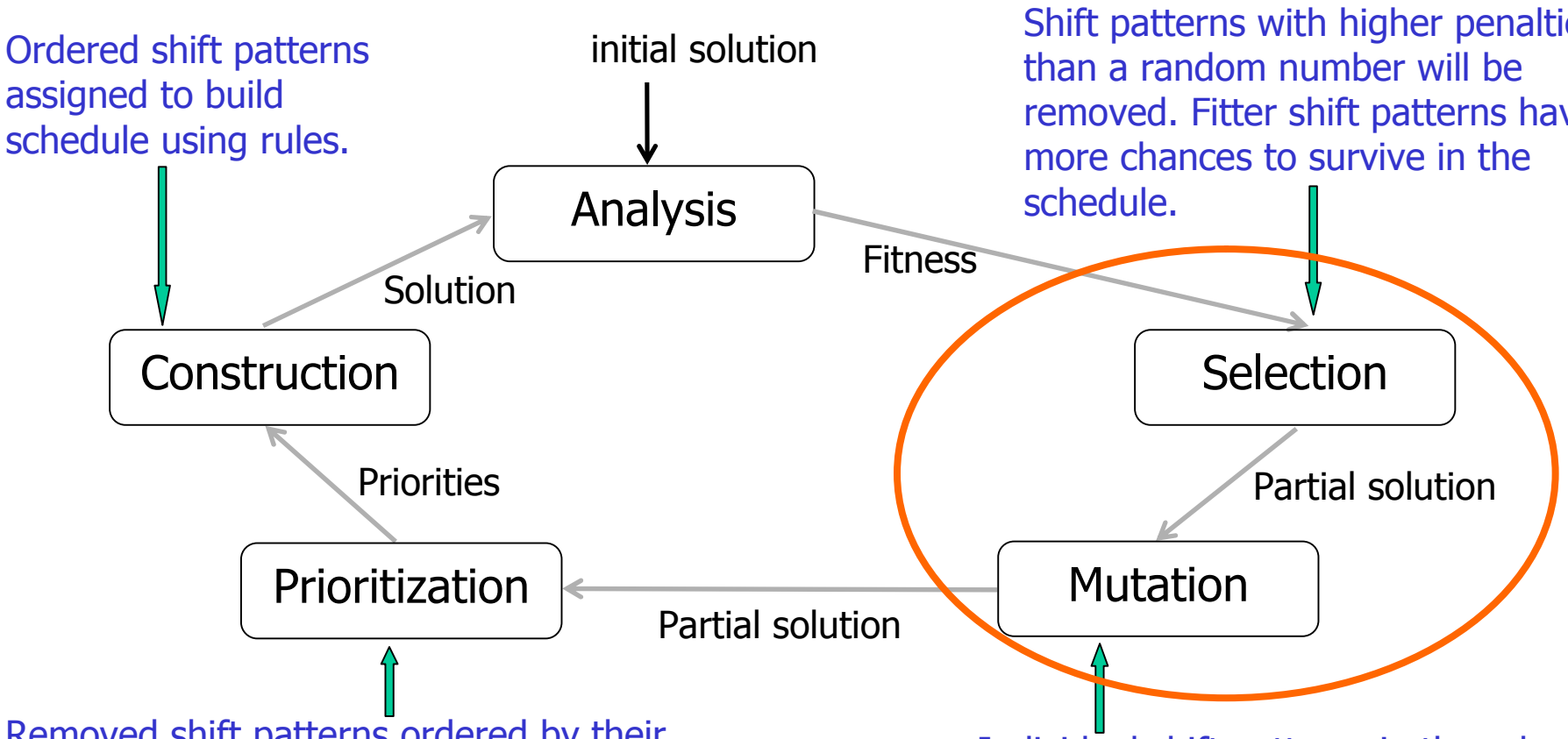


- i – indices of nurses to be allocated a shift pattern
- j – indices of rules to be used in building a schedule
- node N(i,j) – nurse i is scheduled by rule j
- A possible schedule – a directed path from nurse *1* to nurse *m* connecting m nodes

Rule Based Hyper-heuristics

- 6 rules at low level to select shift patterns
  - Random
  - *K*-Cheapest
  - Highest Undercover
  - Overall Cover
  - Contribution-A
  - Contribution-B

Rule Based Hyper-heuristics



Rule Based Hyper-heuristics

- Conclusions
  - Better than an Ant Algorithm previously developed
  - Ant Algorithm performed better than most of the previously developed Genetic Algorithms
  - Slightly worse than Integer Programming, which takes much more time to find optimal solutions

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Questions/Discussions?

- Nurse rostering problems
  - Related variants in ATOSS?
  - …
- Recent Approaches
  - Other related work
  - …