An Investigation of Generic Approaches to LNS

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- Introduction
- Related Work
- Improved Variable-Relationship Guided
- Problems
  - Steel Mill Slab Problem
  - Car Sequencing Problem
  - Machine Reassignment Problem
- Result

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Introduction

Large Neighbourhood Search (LNS) has been demonstrated to be extremely powerful approach in numerous application types

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- Success often depends on experts designing **domain-specific** heuristics for **neighbourhood selection**
- **Heuristics** are often not easily **transferable** between **domains**.

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The goal of our work was to develop a **generic neighbourhood selection operator** that performs well across multiple problem types

What makes a good neighbourhood operator?

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- **No Search Space:**
  - **Domains** of relaxed variables are **reduced** to their **solution values** after **propagation**.
  - Limited scope for improvement.
- **Too Much Search Space:**
  - **No propagation** effects from assignments.
  - Search space is **vast** and **disconnected**.
  - Leads to **brute-force** search over every **domain value**, inefficacious and time-consuming.

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What we want in a neighbourhood:

- **Scope for Improvement:**
  - Uses variables **sharing constraints** to create **connected neighbourhood** that supports effective **propagation**.
  - Enables **efficient exploration** without excessive **domain reduction**.
  - Focuses on variables **likely** to **improve** the objective value.
- **Strong Diversification:**
  - Avoids **repetitive** selections to prevent **stagnation**.

Content

Related Work

Propagation Guided

- Proposed by Perron, Shaw and Furnon in 2004
- Uses **propagation information** to identify strongly **connected neighbourhood**
- The authors found **interleaving** the following three neighbourhood **heuristics** to work best:
  - **PG-LNS**: Start with **all variables unassigned**, and iteratively **freezes variables** until neighbourhood size
  - **Reverse PG-LNS**: Start with **all variables fixed**, and progressively **relaxes variables** until neighbourhood size
  - **Pure random**

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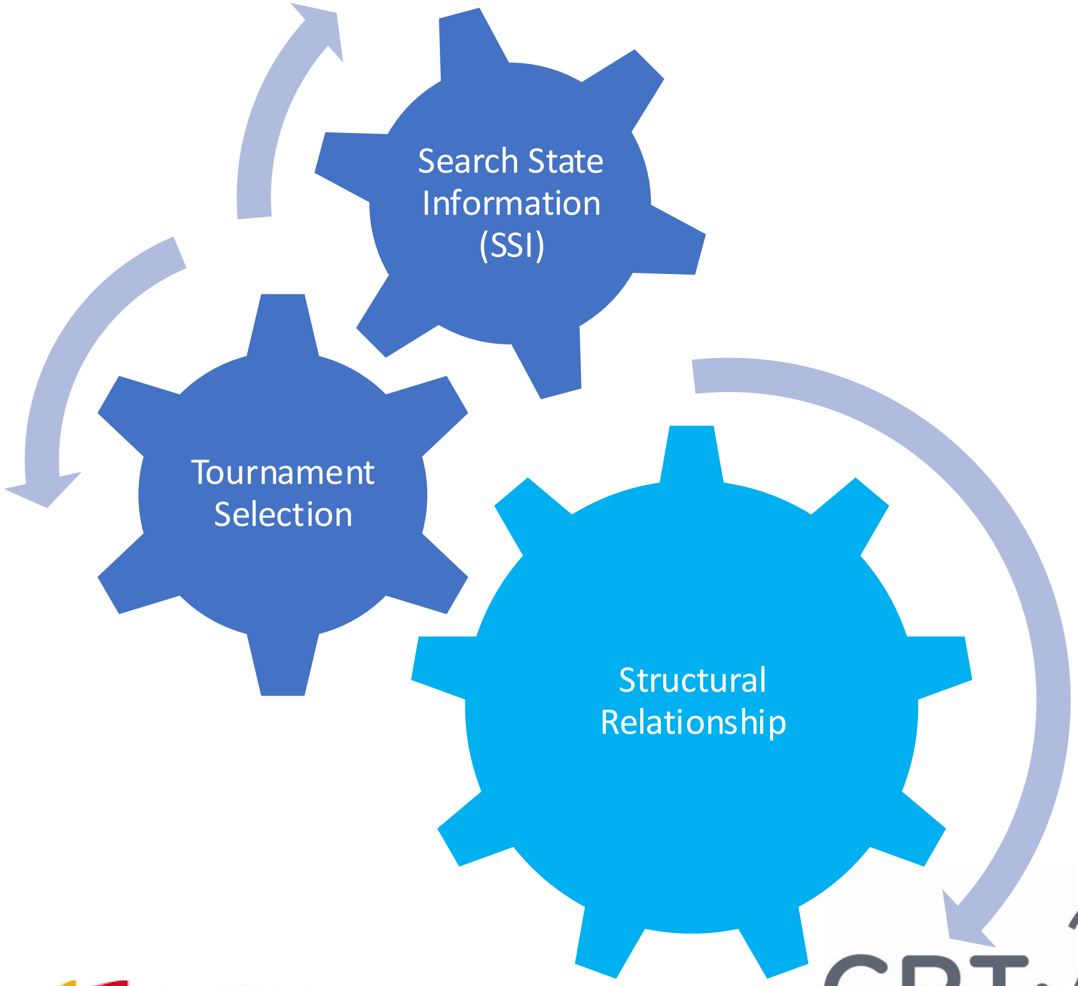
Cost Impact Guided

- Proposed by Lombardi and Schaus in 2014
- Selects variables for relaxation based on their **impact on the cost**
- The cost impact is determined by the **variations** in the **lower bound** that occur when each **variable** is **assigned** a value
- The variations are captured through the **dives** of the **current solution** in a **rearranged order**

Content

Improved Variable-Relationship Guided LNS

- Exploits the **structural relationship** between variables to guide the search process towards **connected neighbourhoods**



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Improved Variable-Relationship Guided LNS

- Exploits the **structural relationship** between variables to guide the search process towards **connected neighbourhoods**
- Combines it with **dynamic information** that describes the **variables states** along search
- Uses **Tournament selection** to boost **diversification** and **reduces computational effort** by focusing on finding the best candidates from a subset, rather than from the entire set of variables.

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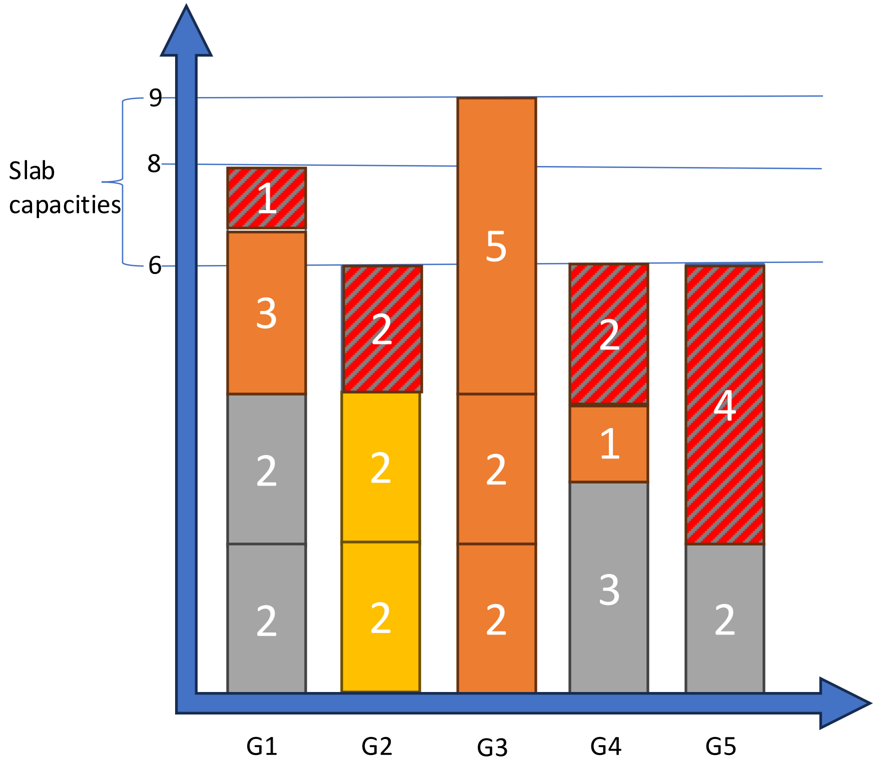
Steel Mill Slab Problem (SMSP)

- Involves to **assign steel orders to slabs** while **minimising** slab **wastage**
- Each **slab** has a **maximum** weight **capacity**
- **Orders** have specific **weight** and **colour**
- This problem was used in the original **Cost Impact Guided paper**



Car Sequencing Problem(CSP)

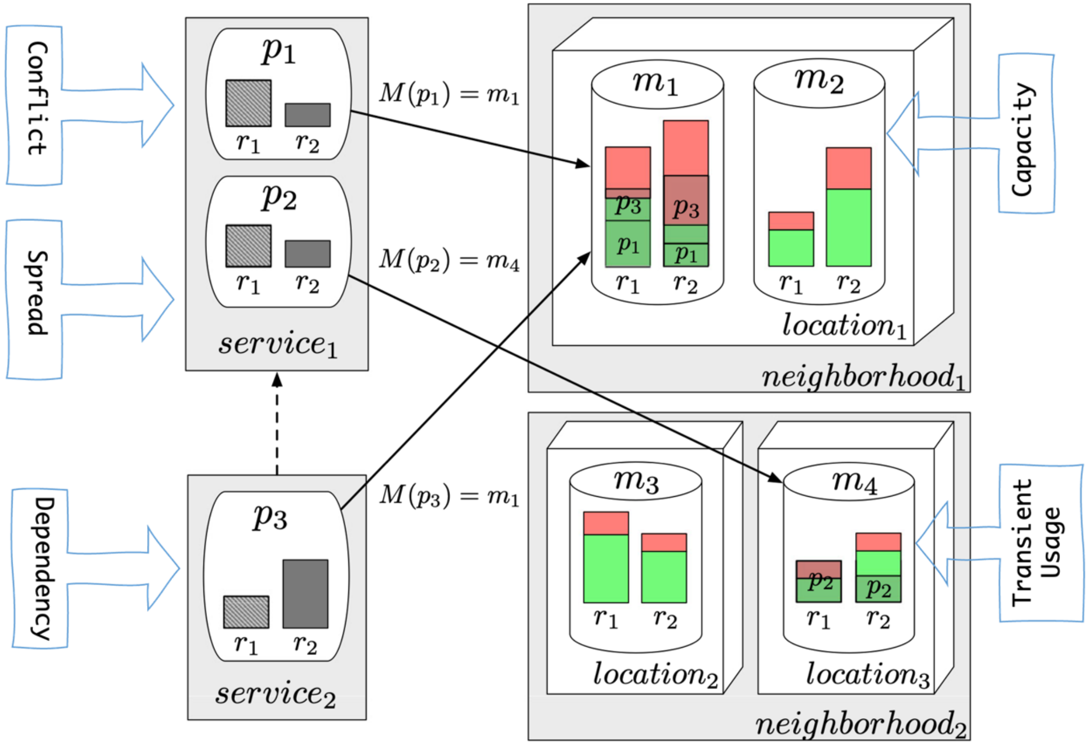
- **Allocates** a set of **cars** on a **production line** of options' installation over a **fixed number of timeslots**
- Each **option installation bay** has its **own capacity**
- **Minimise** the number of **options not placed** on the production line
- This problem was used in the original **Propagation Guided paper**

Work area for Panoramic Roof	Work area for Cruise Control
Capacity Constraint: 2/4	*Capacity Constraint: 2/3*

Options	Model A	Model B	Model C	Model D
Cruise Control	✓	✗	✓	✗
Smart phone integration	✗	✓	✓	✓
Air Conditioning	✓	✗	✗	✓
Automatic transmission	✗	✓	✗	✓
Panoramic Roof	✗	✓	✓	✗
Number of cars required:	30	30	20	40

Machine Reassignment Problem (MRP)

- Proposed by Google in 2012
- Given a **current assignment** of **processes** to **machines** in a data centre
- The goal is to **reassign** some of those **processes** in order to:
    - Improve the **machines usage**
    - Minimise the **overload risks**
    - Minimise the **number** of changes
    - Minimise the **complexity** of **changes**
- Subject to a set of constraint:
    - Capacity
    - Conflict
    - Spread
    - Dependency
    - Transient Usage



Structural Relationship

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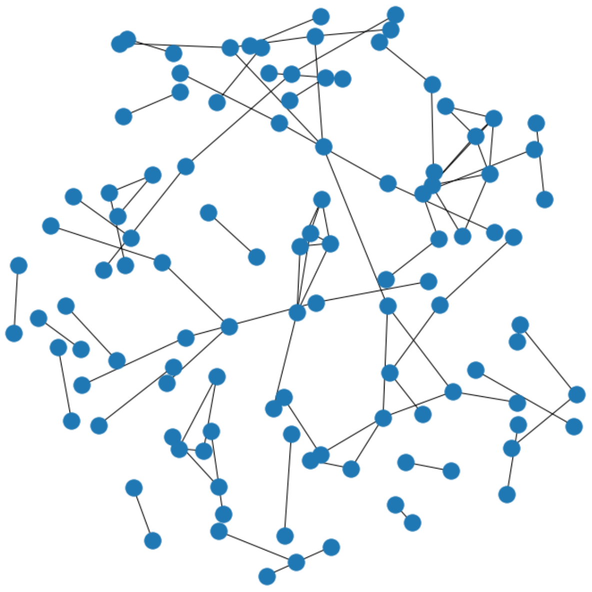
Steel Mill Slab Problem



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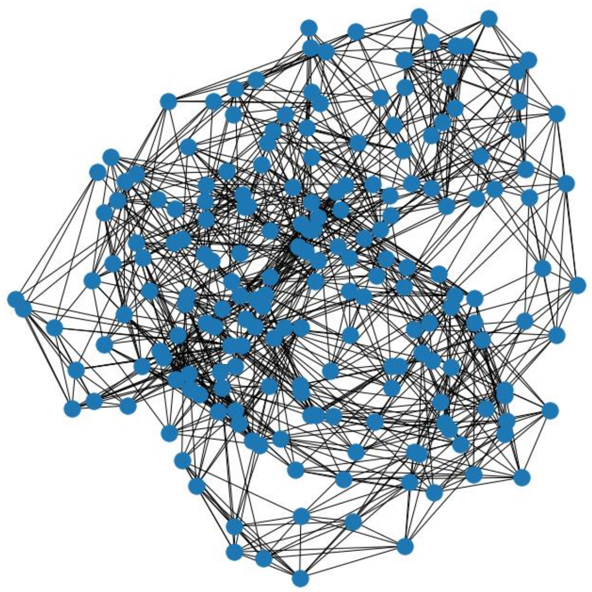

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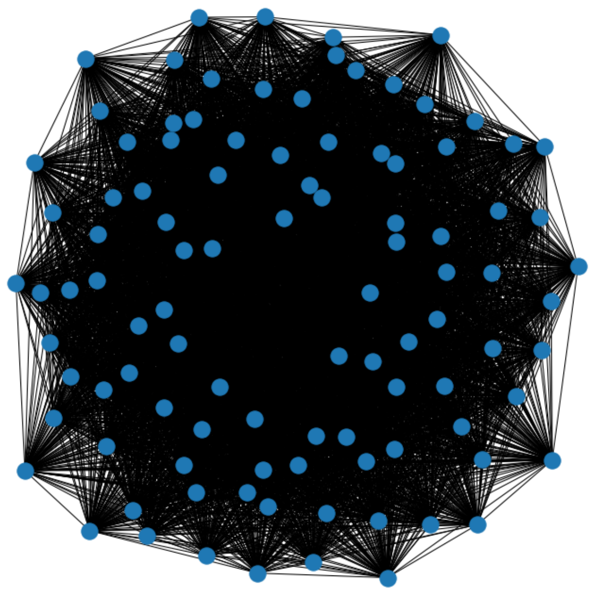


Content

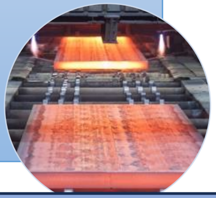
Datasets

140 Instances

Datasets

- Slabs size 2
  - Domain/Variables: 111
- Slabs size 3
  - Domain/Variables: 111
- Slabs size 4
  - Domain/Variables: 111
- Slabs size 5
  - Domain/Variables: 111

80 SMSP



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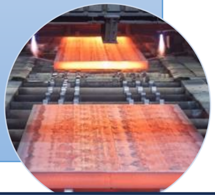

- 200 Cars:
  - Domain/Variables: 200
- 300 cars:
  - Domain/Variables: 300
- 400 cars:
  - Domain/Variables: 400

30 CSP

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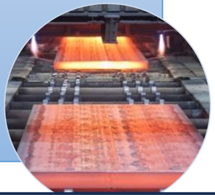

- 200 Cars:
  - Domain/Variables: 200
- 300 cars:
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30 CSP

- Set A:
  - Domain: Up to 100
  - Variables: Up to 1000
- Set B:
  - Variables: Up to 50,000
  - Domain: Up to 5,000
- Set X:
  - Variables: Up to 50,000
  - Domain: Up to 5,000

30 MRP

140 Instances

Metrics

Score

- The same metric used in the **ROADEF EURO Challenge 2012**
- Measures the **distance** the solution found is **from** the **BK**
- **Considers** how much **improvement** was made **from** the **initial solution**

$$((Cost - BK)/initialCost) * 100$$

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Similarity

- The **average** percentage of **intersection** observed across the first **1,000 iterations** of the LNS

$$Similarity = \frac{1}{\binom{1000}{2}} \sum_{i=0}^{999} \sum_{j=i+1}^{999} \frac{|N[i] \cap N[j]|}{|N[i]|}$$

Experiments

- Comparison of generic heuristics:
  - **Rand** - Pure random neighbourhood selection
  - **PG** - Interleaved PG-LNS, Reverse PG-LNS, Rand
  - **CIG** - Cost-Impact Guided
  - **iVRG** - Improved Variable Relationship Guided

Benchmark

Problem	Group	Score				Similarity				#Iterations (x1000)			
		Rand	PG	CIG	iVRG	Rand	PG	CIG	iVRG	Rand	PG	CIG	iVRG
SMSP	2	10.23%	10.24%	10.79%	**5.51%**	**9.01%**	10.10%	9.62%	10.24%	1.7	1.7	1.6	**4.4**
	3	10.80%	11.81%	11.59%	**5.17%**	**9.01%**	10.06%	9.76%	10.26%	2.0	1.9	1.9	**4.3**
	4	5.51%	5.97%	5.68%	**2.81%**	**9.01%**	10.11%	9.85%	10.12%	2.3	2.3	2.3	**7.6**
	5	4.78%	5.57%	4.58%	**2.13%**	**9.01%**	10.17%	10.05%	10.08%	2.7	2.7	2.6	**7.6**
	Overall	7.83%	8.40%	8.16%	**3.91%**	**9.01%**	10.11%	9.82%	10.17%	2.2	2.1	2.1	**6.0**
CSP	200	9.71%	5.36%	8.97%	**4.43%**	**5.00%**	5.01%	5.26%	5.51%	78.2	12.7	**131.7**	18.4
	300	10.36%	5.46%	9.57%	**3.83%**	**3.33%**	3.34%	3.44%	3.64%	52.4	9.1	**87.3**	12.8
	400	11.58%	5.67%	10.11%	**3.86%**	2.50%	**2.50%**	2.55%	2.72%	32.9	6.3	**55.5**	9.1
	Overall	10.55%	5.50%	9.55%	**4.04%**	**3.61%**	3.61%	3.75%	3.95%	54.5	9.3	**91.5**	13.4
MRP	A	3.69%	5.25%	3.17%	**2.33%**	**4.56%**	5.11%	8.80%	5.06%	87.3	7.6	**98.7**	70.1
	B	0.31%	0.94%	0.36%	**0.26%**	**0.26%**	0.26%	3.14%	0.35%	**52.2**	0.8	13.6	44.0
	X	0.46%	0.62%	0.41%	**0.34%**	0.29%	**0.25%**	3.69%	0.38%	**53.9**	0.8	15.7	34.9
	Overall	1.49%	2.27%	1.31%	**0.98%**	**1.70%**	1.87%	5.21%	1.93%	**64.5**	3.0	42.7	49.7

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	400	11.58%	5.67%	10.11%	**3.86%**	2.50%	**2.50%**	2.55%	2.72%	32.9	6.3	**55.5**	9.1
	Overall	10.55%	5.50%	9.55%	**4.04%**	**3.61%**	3.61%	3.75%	3.95%	54.5	9.3	**91.5**	13.4
MRP	A	3.69%	5.25%	3.17%	**2.33%**	**4.56%**	5.11%	8.80%	5.06%	87.3	7.6	**98.7**	70.1
	B	0.31%	0.94%	0.36%	**0.26%**	**0.26%**	0.26%	3.14%	0.35%	**52.2**	0.8	13.6	44.0
	X	0.46%	0.62%	0.41%	**0.34%**	0.29%	**0.25%**	3.69%	0.38%	**53.9**	0.8	15.7	34.9
	Overall	1.49%	2.27%	1.31%	**0.98%**	**1.70%**	1.87%	5.21%	1.93%	**64.5**	3.0	42.7	49.7

Benchmark

Problem	Group	Score				Similarity				#Iterations (x1000)			
		Rand	PG	CIG	iVRG	Rand	PG	CIG	iVRG	Rand	PG	CIG	iVRG
SMSP	2	10.23%	10.24%	10.79%	**5.51%**	**9.01%**	10.10%	9.62%	10.24%	1.7	1.7	1.6	**4.4**
	3	10.80%	11.81%	11.59%	**5.17%**	**9.01%**	10.06%	9.76%	10.26%	2.0	1.9	1.9	**4.3**
	4	5.51%	5.97%	5.68%	**2.81%**	**9.01%**	10.11%	9.85%	10.12%	2.3	2.3	2.3	**7.6**
	5	4.78%	5.57%	4.58%	**2.13%**	**9.01%**	10.17%	10.05%	10.08%	2.7	2.7	2.6	**7.6**
	Overall	7.83%	8.40%	8.16%	**3.91%**	**9.01%**	10.11%	9.82%	10.17%	2.2	2.1	2.1	**6.0**
CSP	200	9.71%	5.36%	8.97%	**4.43%**	**5.00%**	5.01%	5.26%	5.51%	78.2	12.7	**131.7**	18.4
	300	10.36%	5.46%	9.57%	**3.83%**	**3.33%**	3.34%	3.44%	3.64%	52.4	9.1	**87.3**	12.8
	400	11.58%	5.67%	10.11%	**3.86%**	2.50%	**2.50%**	2.55%	2.72%	32.9	6.3	**55.5**	9.1
	Overall	10.55%	5.50%	9.55%	**4.04%**	**3.61%**	3.61%	3.75%	3.95%	54.5	9.3	**91.5**	13.4
MRP	A	3.69%	5.25%	3.17%	**2.33%**	**4.56%**	5.11%	8.80%	5.06%	87.3	7.6	**98.7**	70.1
	B	0.31%	0.94%	0.36%	**0.26%**	**0.26%**	0.26%	3.14%	0.35%	**52.2**	0.8	13.6	44.0
	X	0.46%	0.62%	0.41%	**0.34%**	0.29%	**0.25%**	3.69%	0.38%	**53.9**	0.8	15.7	34.9
	Overall	1.49%	2.27%	1.31%	**0.98%**	**1.70%**	1.87%	5.21%	1.93%	**64.5**	3.0	42.7	49.7

Experiments

- Comparison of generic heuristics:
  - **Rand** - Pure random neighbourhood selection
  - **PG** - Interleaved PG-LNS, Reverse PG-LNS, Rand
  - **CIG** - Cost-Impact Guided
  - **iVRG** - Improved Variable Relationship Guided
- Comparison of iVRG components:
  - **NonT** – iVRG without tournament selection (so chooses amongst all variables)
  - **NonS** – iVRG without using search state information (so chooses randomly amongst tournament of variables related to previous selected)
  - **NonR** – iVRG without variable relationship (so each tournament is just consisting of randomly selected variables, one with best SSI chosen)

iVRG Components

Problem	Group	Score				Similarity				#Iterations (x1000)			
		iVRG	NonT	NonS	NonR	iVRG	NonT	NonS	NonR	iVRG	NonT	NonS	NonR
SMSP	2	**5.51%**	6.23%	6.24%	10.38%	10.24%	9.92%	**9.82%**	22.42%	**4.4**	4.3	4.1	1.8
	3	5.17%	**4.93%**	5.34%	14.41%	10.26%	10.03%	**9.96%**	21.57%	4.3	**4.5**	4.4	2.1
	4	2.81%	**2.79%**	2.82%	13.68%	10.12%	9.88%	**9.85%**	21.27%	7.6	7.9	**8.0**	2.1
	5	2.13%	**2.06%**	2.28%	17.38%	10.08%	9.90%	**9.84%**	20.97%	7.6	**8.0**	7.4	1.9
	Overall	**3.91%**	4.00%	4.17%	13.96%	10.17%	9.93%	**9.87%**	21.56%	6.0	**6.2**	6.0	2.0
CSP	200	**4.43%**	10.47%	4.50%	9.59%	5.51%	12.57%	**5.02%**	6.03%	18.4	14.1	14.2	**86.8**
	300	**3.83%**	11.11%	4.28%	10.71%	3.64%	10.92%	**3.35%**	4.02%	12.8	9.7	9.9	**56.1**
	400	**3.86%**	9.57%	3.87%	11.32%	2.72%	7.21%	**2.50%**	3.06%	9.1	6.1	7.4	**34.9**
	Overall	**4.04%**	10.38%	4.22%	10.54%	3.95%	10.23%	**3.62%**	4.37%	13.4	10.0	10.5	**59.3**
MRP	A	**2.33%**	6.04%	2.66%	5.85%	5.06%	23.83%	**4.75%**	10.90%	70.1	65.4	63.1	**91.2**
	B	**0.26%**	0.74%	0.29%	0.39%	0.35%	20.10%	**0.28%**	0.61%	44.0	8.5	44.9	**57.0**
	X	**0.34%**	0.90%	0.37%	0.46%	0.38%	20.83%	**0.31%**	0.67%	34.9	7.2	40.8	**89.2**
	Overall	**0.98%**	2.56%	1.11%	2.23%	1.93%	21.59%	**1.78%**	4.06%	49.7	27.0	49.6	**79.1**

iVRG Components

Problem	Group	Score				Similarity				#Iterations (x1000)			
		iVRG	NonT	NonS	NonR	iVRG	NonT	NonS	NonR	iVRG	NonT	NonS	NonR
SMSP	2	**5.51%**	6.23%	6.24%	10.38%	10.24%	9.92%	**9.82%**	22.42%	**4.4**	4.3	4.1	1.8
	3	5.17%	**4.93%**	5.34%	14.41%	10.26%	10.03%	**9.96%**	21.57%	4.3	**4.5**	4.4	2.1
	4	2.81%	**2.79%**	2.82%	13.68%	10.12%	9.88%	**9.85%**	21.27%	7.6	7.9	**8.0**	2.1
	5	2.13%	**2.06%**	2.28%	17.38%	10.08%	9.90%	**9.84%**	20.97%	7.6	**8.0**	7.4	1.9
	Overall	**3.91%**	4.00%	4.17%	13.96%	10.17%	9.93%	**9.87%**	21.56%	6.0	**6.2**	6.0	2.0
CSP	200	**4.43%**	10.47%	4.50%	9.59%	5.51%	12.57%	**5.02%**	6.03%	18.4	14.1	14.2	**86.8**
	300	**3.83%**	11.11%	4.28%	10.71%	3.64%	10.92%	**3.35%**	4.02%	12.8	9.7	9.9	**56.1**
	400	**3.86%**	9.57%	3.87%	11.32%	2.72%	7.21%	**2.50%**	3.06%	9.1	6.1	7.4	**34.9**
	Overall	**4.04%**	10.38%	4.22%	10.54%	3.95%	10.23%	**3.62%**	4.37%	13.4	10.0	10.5	**59.3**
MRP	A	**2.33%**	6.04%	2.66%	5.85%	5.06%	23.83%	**4.75%**	10.90%	70.1	65.4	63.1	**91.2**
	B	**0.26%**	0.74%	0.29%	0.39%	0.35%	20.10%	**0.28%**	0.61%	44.0	8.5	44.9	**57.0**
	X	**0.34%**	0.90%	0.37%	0.46%	0.38%	20.83%	**0.31%**	0.67%	34.9	7.2	40.8	**89.2**
	Overall	**0.98%**	2.56%	1.11%	2.23%	1.93%	21.59%	**1.78%**	4.06%	49.7	27.0	49.6	**79.1**

iVRG Components

Problem	Group	Score				Similarity				#Iterations (x1000)			
		iVRG	NonT	NonS	NonR	iVRG	NonT	NonS	NonR	iVRG	NonT	NonS	NonR
SMSP	2	**5.51%**	6.23%	6.24%	10.38%	10.24%	9.92%	**9.82%**	22.42%	**4.4**	4.3	4.1	1.8
	3	5.17%	**4.93%**	5.34%	14.41%	10.26%	10.03%	**9.96%**	21.57%	4.3	**4.5**	4.4	2.1
	4	2.81%	**2.79%**	2.82%	13.68%	10.12%	9.88%	**9.85%**	21.27%	7.6	7.9	**8.0**	2.1
	5	2.13%	**2.06%**	2.28%	17.38%	10.08%	9.90%	**9.84%**	20.97%	7.6	**8.0**	7.4	1.9
	Overall	**3.91%**	4.00%	4.17%	13.96%	10.17%	9.93%	**9.87%**	21.56%	6.0	**6.2**	6.0	2.0
CSP	200	**4.43%**	10.47%	4.50%	9.59%	5.51%	12.57%	**5.02%**	6.03%	18.4	14.1	14.2	**86.8**
	300	**3.83%**	11.11%	4.28%	10.71%	3.64%	10.92%	**3.35%**	4.02%	12.8	9.7	9.9	**56.1**
	400	**3.86%**	9.57%	3.87%	11.32%	2.72%	7.21%	**2.50%**	3.06%	9.1	6.1	7.4	**34.9**
	Overall	**4.04%**	10.38%	4.22%	10.54%	3.95%	10.23%	**3.62%**	4.37%	13.4	10.0	10.5	**59.3**
MRP	A	**2.33%**	6.04%	2.66%	5.85%	5.06%	23.83%	**4.75%**	10.90%	70.1	65.4	63.1	**91.2**
	B	**0.26%**	0.74%	0.29%	0.39%	0.35%	20.10%	**0.28%**	0.61%	44.0	8.5	44.9	**57.0**
	X	**0.34%**	0.90%	0.37%	0.46%	0.38%	20.83%	**0.31%**	0.67%	34.9	7.2	40.8	**89.2**
	Overall	**0.98%**	2.56%	1.11%	2.23%	1.93%	21.59%	**1.78%**	4.06%	49.7	27.0	49.6	**79.1**

iVRG Components

Problem	Group	Score				Similarity				#Iterations (x1000)			
		iVRG	NonT	NonS	NonR	iVRG	NonT	NonS	NonR	iVRG	NonT	NonS	NonR
SMSP	2	**5.51%**	6.23%	6.24%	10.38%	10.24%	9.92%	**9.82%**	22.42%	**4.4**	4.3	4.1	1.8
	3	5.17%	**4.93%**	5.34%	14.41%	10.26%	10.03%	**9.96%**	21.57%	4.3	**4.5**	4.4	2.1
	4	2.81%	**2.79%**	2.82%	13.68%	10.12%	9.88%	**9.85%**	21.27%	7.6	7.9	**8.0**	2.1
	5	2.13%	**2.06%**	2.28%	17.38%	10.08%	9.90%	**9.84%**	20.97%	7.6	**8.0**	7.4	1.9
	Overall	**3.91%**	4.00%	4.17%	13.96%	10.17%	9.93%	**9.87%**	21.56%	6.0	**6.2**	6.0	2.0
CSP	200	**4.43%**	10.47%	4.50%	9.59%	5.51%	12.57%	**5.02%**	6.03%	18.4	14.1	14.2	**86.8**
	300	**3.83%**	11.11%	4.28%	10.71%	3.64%	10.92%	**3.35%**	4.02%	12.8	9.7	9.9	**56.1**
	400	**3.86%**	9.57%	3.87%	11.32%	2.72%	7.21%	**2.50%**	3.06%	9.1	6.1	7.4	**34.9**
	Overall	**4.04%**	10.38%	4.22%	10.54%	3.95%	10.23%	**3.62%**	4.37%	13.4	10.0	10.5	**59.3**
MRP	A	**2.33%**	6.04%	2.66%	5.85%	5.06%	23.83%	**4.75%**	10.90%	70.1	65.4	63.1	**91.2**
	B	**0.26%**	0.74%	0.29%	0.39%	0.35%	20.10%	**0.28%**	0.61%	44.0	8.5	44.9	**57.0**
	X	**0.34%**	0.90%	0.37%	0.46%	0.38%	20.83%	**0.31%**	0.67%	34.9	7.2	40.8	**89.2**
	Overall	**0.98%**	2.56%	1.11%	2.23%	1.93%	21.59%	**1.78%**	4.06%	49.7	27.0	49.6	**79.1**

iVRG Components

Problem	Group	Score				Similarity				#Iterations (x1000)			
		iVRG	NonT	NonS	NonR	iVRG	NonT	NonS	NonR	iVRG	NonT	NonS	NonR
SMSP	2	**5.51%**	6.23%	6.24%	10.38%	10.24%	9.92%	**9.82%**	22.42%	**4.4**	4.3	4.1	1.8
	3	5.17%	**4.93%**	5.34%	14.41%	10.26%	10.03%	**9.96%**	21.57%	4.3	**4.5**	4.4	2.1
	4	2.81%	**2.79%**	2.82%	13.68%	10.12%	9.88%	**9.85%**	21.27%	7.6	7.9	**8.0**	2.1
	5	2.13%	**2.06%**	2.28%	17.38%	10.08%	9.90%	**9.84%**	20.97%	7.6	**8.0**	7.4	1.9
	Overall	**3.91%**	4.00%	4.17%	13.96%	10.17%	9.93%	**9.87%**	21.56%	6.0	**6.2**	6.0	2.0
CSP	200	**4.43%**	10.47%	4.50%	9.59%	5.51%	12.57%	**5.02%**	6.03%	18.4	14.1	14.2	**86.8**
	300	**3.83%**	11.11%	4.28%	10.71%	3.64%	10.92%	**3.35%**	4.02%	12.8	9.7	9.9	**56.1**
	400	**3.86%**	9.57%	3.87%	11.32%	2.72%	7.21%	**2.50%**	3.06%	9.1	6.1	7.4	**34.9**
	Overall	**4.04%**	10.38%	4.22%	10.54%	3.95%	10.23%	**3.62%**	4.37%	13.4	10.0	10.5	**59.3**
MRP	A	**2.33%**	6.04%	2.66%	5.85%	5.06%	23.83%	**4.75%**	10.90%	70.1	65.4	63.1	**91.2**
	B	**0.26%**	0.74%	0.29%	0.39%	0.35%	20.10%	**0.28%**	0.61%	44.0	8.5	44.9	**57.0**
	X	**0.34%**	0.90%	0.37%	0.46%	0.38%	20.83%	**0.31%**	0.67%	34.9	7.2	40.8	**89.2**
	Overall	**0.98%**	2.56%	1.11%	2.23%	1.93%	21.59%	**1.78%**	4.06%	49.7	27.0	49.6	**79.1**

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iVRG Components

Problem	Group	Score				Similarity				#Iterations (x1000)			
		iVRG	NonT	NonS	NonR	iVRG	NonT	NonS	NonR	iVRG	NonT	NonS	NonR
SMSP	2	**5.51%**	6.23%	6.24%	10.38%	10.24%	9.92%	**9.82%**	22.42%	**4.4**	4.3	4.1	1.8
	3	5.17%	**4.93%**	5.34%	14.41%	10.26%	10.03%	**9.96%**	21.57%	4.3	**4.5**	4.4	2.1
	4	2.81%	**2.79%**	2.82%	13.68%	10.12%	9.88%	**9.85%**	21.27%	7.6	7.9	**8.0**	2.1
	5	2.13%	**2.06%**	2.28%	17.38%	10.08%	9.90%	**9.84%**	20.97%	7.6	**8.0**	7.4	1.9
	Overall	**3.91%**	4.00%	4.17%	13.96%	10.17%	9.93%	**9.87%**	21.56%	6.0	**6.2**	6.0	2.0
	200	**4.43%**	10.47%	4.50%	9.59%	5.51%	12.57%	**5.02%**	6.03%	18.4	14.1	14.2	**86.8**

Problem	Group	Score				Similarity				#Iterations (x1000)			
		Rand	PG	CIG	iVRG	Rand	PG	CIG	iVRG	Rand	PG	CIG	iVRG
SMSP	2	10.23%	10.24%	10.79%	**5.51%**	**9.01%**	10.10%	9.62%	10.24%	1.7	1.7	1.6	**4.4**
	3	10.80%	11.81%	11.59%	**5.17%**	**9.01%**	10.06%	9.76%	10.26%	2.0	1.9	1.9	**4.3**
	4	5.51%	5.97%	5.68%	**2.81%**	**9.01%**	10.11%	9.85%	10.12%	2.3	2.3	2.3	**7.6**
	5	4.78%	5.57%	4.58%	**2.13%**	**9.01%**	10.17%	10.05%	10.08%	2.7	2.7	2.6	**7.6**
	Overall	7.83%	8.40%	8.16%	**3.91%**	**9.01%**	10.11%	9.82%	10.17%	2.2	2.1	2.1	**6.0**
	200	9.71%	5.36%	8.97%	**4.43%**	**5.00%**	5.01%	5.26%	5.51%	78.2	12.7	**131.7**	18.4

iVRG Components

Problem	Group	Score				Similarity				#Iterations (x1000)			
		iVRG	NonT	NonS	NonR	iVRG	NonT	NonS	NonR	iVRG	NonT	NonS	NonR
SMSP	2	**5.51%**	6.23%	6.24%	10.38%	10.24%	9.92%	**9.82%**	22.42%	**4.4**	4.3	4.1	1.8
	3	5.17%	**4.93%**	5.34%	14.41%	10.26%	10.03%	**9.96%**	21.57%	4.3	**4.5**	4.4	2.1
	4	2.81%	**2.79%**	2.82%	13.68%	10.12%	9.88%	**9.85%**	21.27%	7.6	7.9	**8.0**	2.1
	5	2.13%	**2.06%**	2.28%	17.38%	10.08%	9.90%	**9.84%**	20.97%	7.6	**8.0**	7.4	1.9
	Overall	**3.91%**	4.00%	4.17%	13.96%	10.17%	9.93%	**9.87%**	21.56%	6.0	**6.2**	6.0	2.0
CSP	200	**4.43%**	10.47%	4.50%	9.59%	5.51%	12.57%	**5.02%**	6.03%	18.4	14.1	14.2	**86.8**
	300	**3.83%**	11.11%	4.28%	10.71%	3.64%	10.92%	**3.35%**	4.02%	12.8	9.7	9.9	**56.1**
	400	**3.86%**	9.57%	3.87%	11.32%	2.72%	7.21%	**2.50%**	3.06%	9.1	6.1	7.4	**34.9**
	Overall	**4.04%**	10.38%	4.22%	10.54%	3.95%	10.23%	**3.62%**	4.37%	13.4	10.0	10.5	**59.3**
MRP	A	**2.33%**	6.04%	2.66%	5.85%	5.06%	23.83%	**4.75%**	10.90%	70.1	65.4	63.1	**91.2**
	B	**0.26%**	0.74%	0.29%	0.39%	0.35%	20.10%	**0.28%**	0.61%	44.0	8.5	44.9	**57.0**
	X	**0.34%**	0.90%	0.37%	0.46%	0.38%	20.83%	**0.31%**	0.67%	34.9	7.2	40.8	**89.2**
	Overall	**0.98%**	2.56%	1.11%	2.23%	1.93%	21.59%	**1.78%**	4.06%	49.7	27.0	49.6	**79.1**

iVRG Components

Problem	Group	Score				Similarity				#Iterations (x1000)			
		iVRG	NonT	NonS	NonR	iVRG	NonT	NonS	NonR	iVRG	NonT	NonS	NonR
SMSP	2	**5.51%**	6.23%	6.24%	10.38%	10.24%	9.92%	**9.82%**	22.42%	**4.4**	4.3	4.1	1.8
	3	5.17%	**4.93%**	5.34%	14.41%	10.26%	10.03%	**9.96%**	21.57%	4.3	**4.5**	4.4	2.1
	4	2.81%	**2.79%**	2.82%	13.68%	10.12%	9.88%	**9.85%**	21.27%	7.6	7.9	**8.0**	2.1
	5	2.13%	**2.06%**	2.28%	17.38%	10.08%	9.90%	**9.84%**	20.97%	7.6	**8.0**	7.4	1.9
	Overall	**3.91%**	4.00%	4.17%	13.96%	10.17%	9.93%	**9.87%**	21.56%	6.0	**6.2**	6.0	2.0
CSP	200	**4.43%**	10.47%	4.50%	9.59%	5.51%	12.57%	**5.02%**	6.03%	18.4	14.1	14.2	**86.8**
	300	**3.83%**	11.11%	4.28%	10.71%	3.64%	10.92%	**3.35%**	4.02%	12.8	9.7	9.9	**56.1**
	400	**3.86%**	9.57%	3.87%	11.32%	2.72%	7.21%	**2.50%**	3.06%	9.1	6.1	7.4	**34.9**
	Overall	**4.04%**	10.38%	4.22%	10.54%	3.95%	10.23%	**3.62%**	4.37%	13.4	10.0	10.5	**59.3**
MRP	A	**2.33%**	6.04%	2.66%	5.85%	5.06%	23.83%	**4.75%**	10.90%	70.1	65.4	63.1	**91.2**
	B	**0.26%**	0.74%	0.29%	0.39%	0.35%	20.10%	**0.28%**	0.61%	44.0	8.5	44.9	**57.0**
	X	**0.34%**	0.90%	0.37%	0.46%	0.38%	20.83%	**0.31%**	0.67%	34.9	7.2	40.8	**89.2**
	Overall	**0.98%**	2.56%	1.11%	2.23%	1.93%	21.59%	**1.78%**	4.06%	49.7	27.0	49.6	**79.1**

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- The empirical evaluation demonstrated the **generalisability** of iVRG
- The **structural Relationship** was the most important aspect, followed closely by **tournament selection**.

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