

# A Sequence-based Selection Hyper-heuristic Utilising a Hidden Markov Model

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# Outline

Introduction

Proposed Method

Case Studies

Summary

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## Search and Optimisation

Search and optimisation algorithms are concerned with the discovery of the best possible solution in a given time to maximise or minimise an objective (or set of objectives).

Most real-world search and optimisation problems cannot be solved exactly, requiring heuristic approaches such as LSs.

Hyper-heuristics aim to automate the search process.

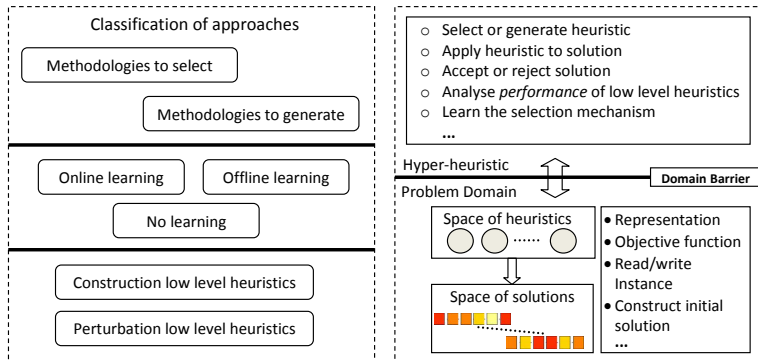
— Burke et al., (2013) for recent survey

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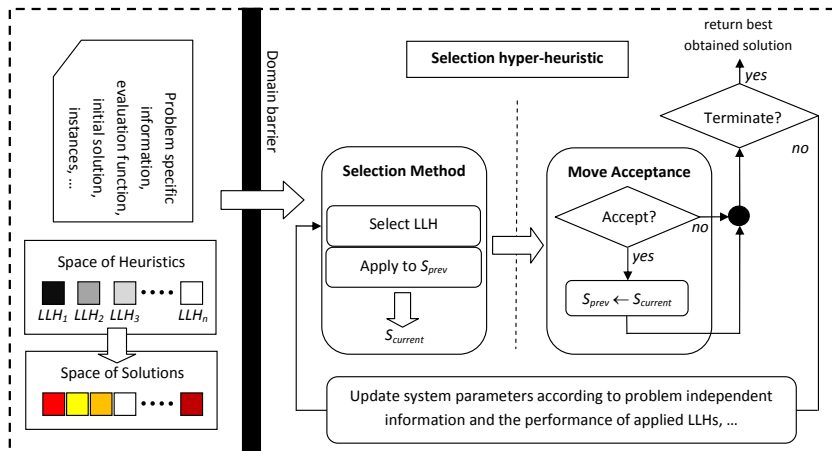
Edmund K. Burke, Michel Gendreau, Matthew Hyde, Graham Kendall, Gabriela Ochoa, Ender Özcan and Rong Qu  
Hyper-heuristics: a survey of the state of the art. *Journal of the Operational Research Society*, 64(12):1695-1724, 2013.

# Hyper-heuristic

“A search method or learning mechanism for *selecting* or *generating* heuristics to solve computational search problems”



# Selection Hyper-heuristic Framework



# Outline

Introduction

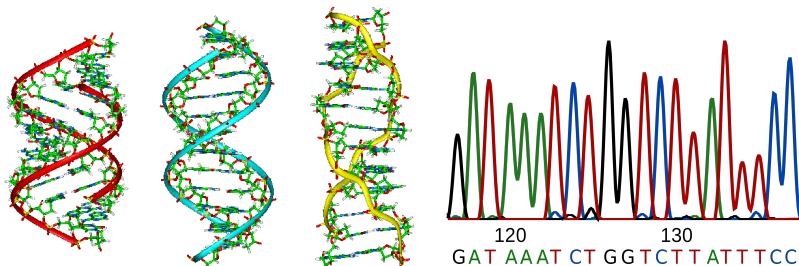
**Proposed Method**

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## Sequence-based Selection Hyper-heuristic

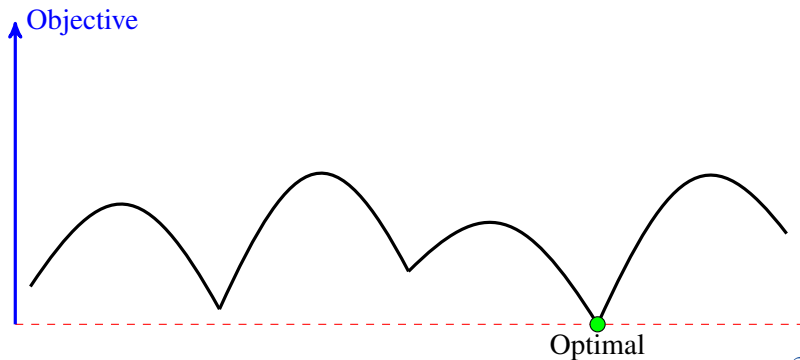
**Key feature:** Sequence-based selection hyper-heuristics aim to analyse the performance of, and construct, sequences of heuristics.





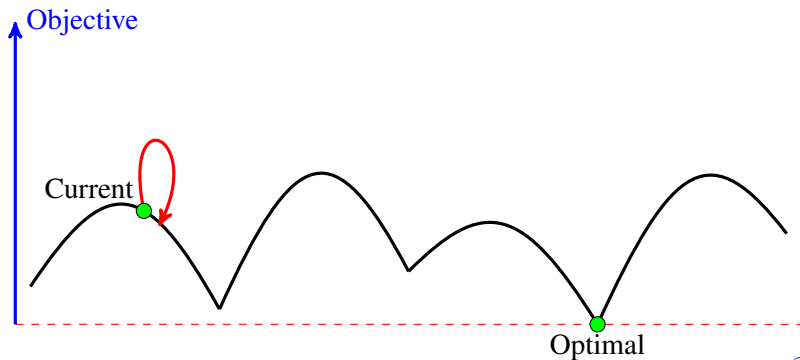
# Fitness Landscape and Low Level Heuristics

Fitness landscape



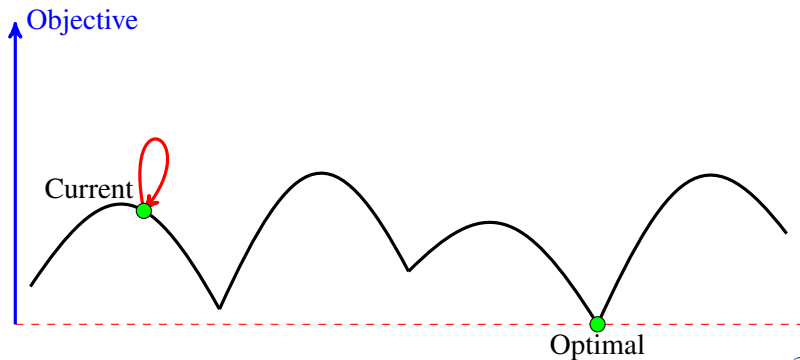
# Fitness Landscape and Low Level Heuristics

Apply a single low level heuristic



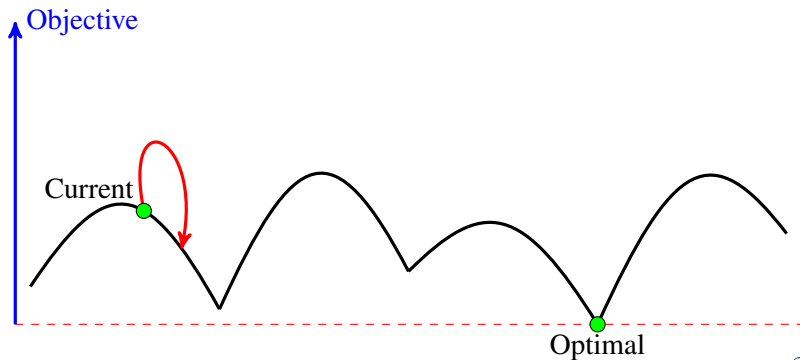
# Fitness Landscape and Low Level Heuristics

Apply a single low level heuristic



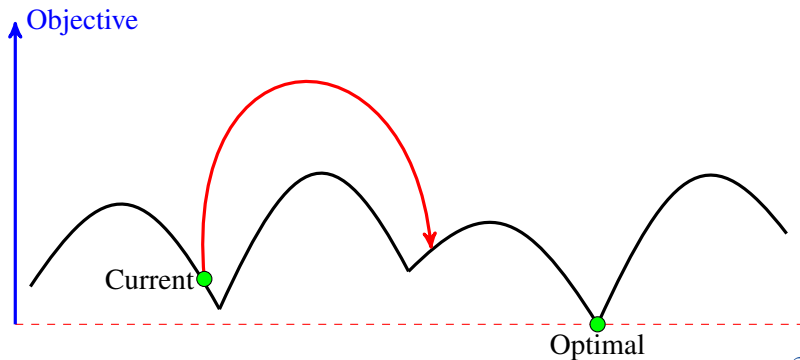
# Fitness Landscape and Low Level Heuristics

Apply a sequence of two low level heuristics

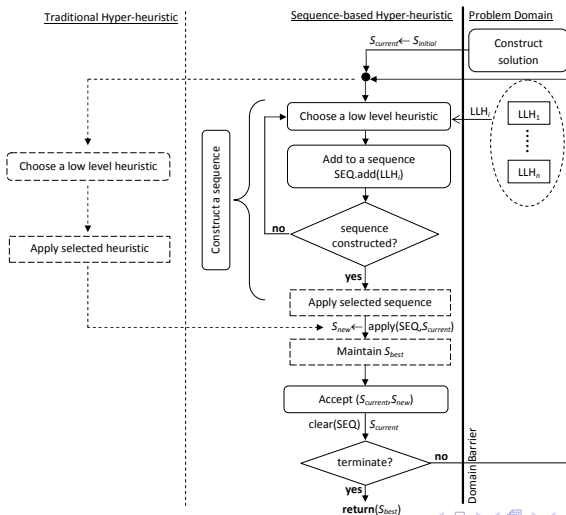


# Fitness Landscape and Low Level Heuristics

Apply a sequence of three or more low level heuristics



# Sequence-based Selection Hyper-heuristic Framework



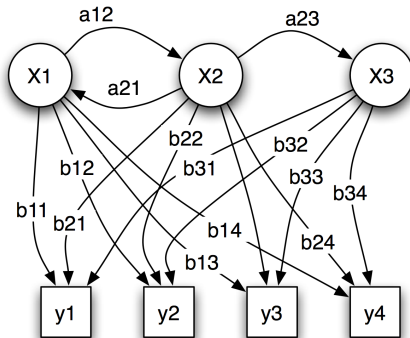
# Hidden Markov Model (HMM)

Transition Matrix

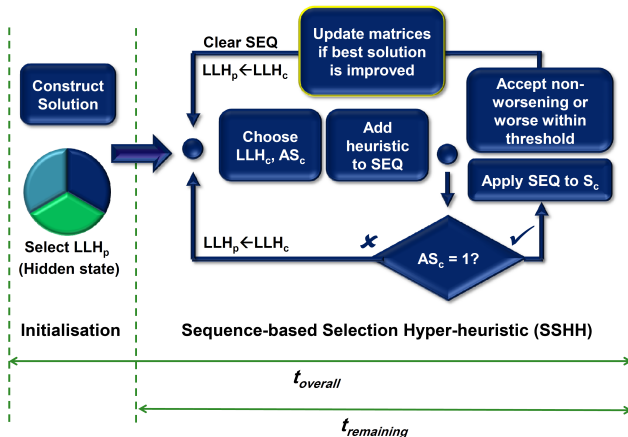
to from	X1	X2	X3
X1	a11	a12	a13
X2	a21	a22	a23
X3	a31	a32	a33

Observation Probability Matrix

	y1	y2	y3	y4
X1	b11	b12	b13	b14
X2	b21	b22	b23	b24
X3	b31	b32	b33	b34



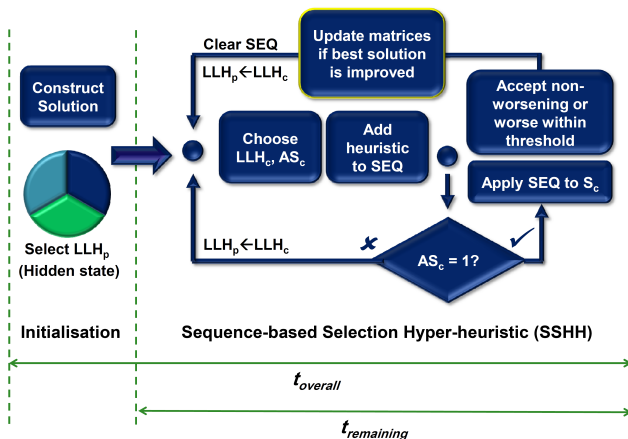
# Sequence-based Hyper-heuristic Utilising HMM



AS: Sequence-based Acceptance Strategy (Observation)

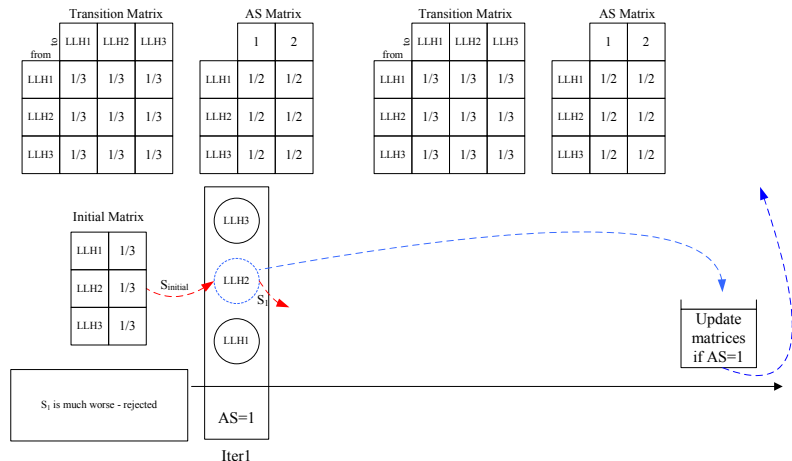


# Sequence-based Hyper-heuristic Utilising HMM

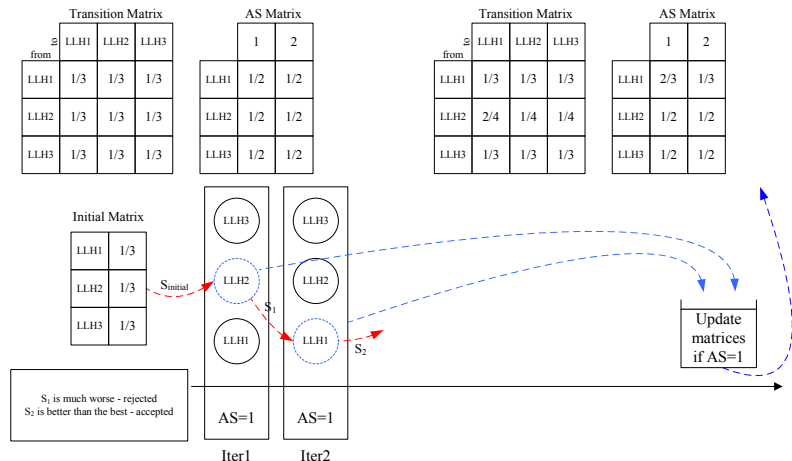


AS: Sequence-based Acceptance Strategy (Observation)

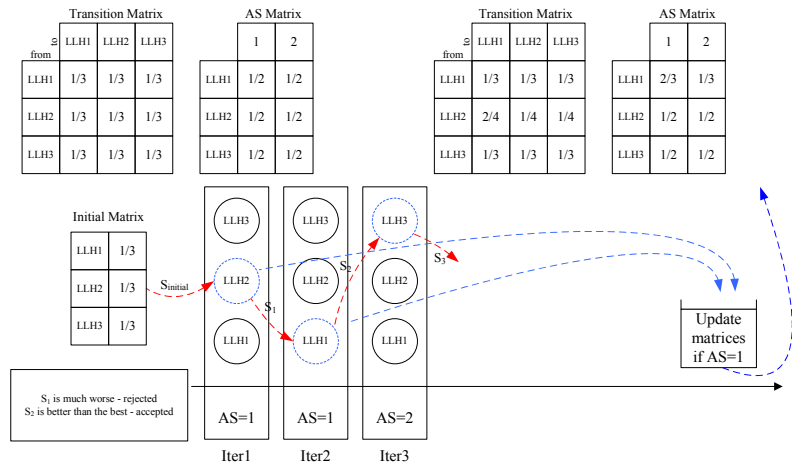
# Sequence-based Hyper-heuristic Utilising HMM



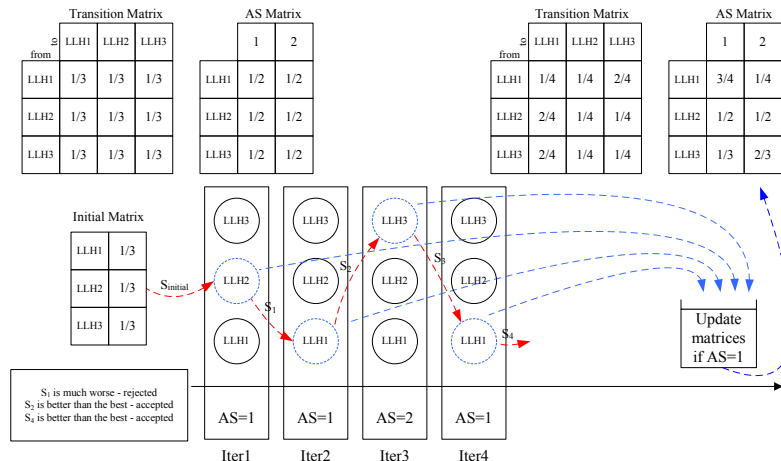
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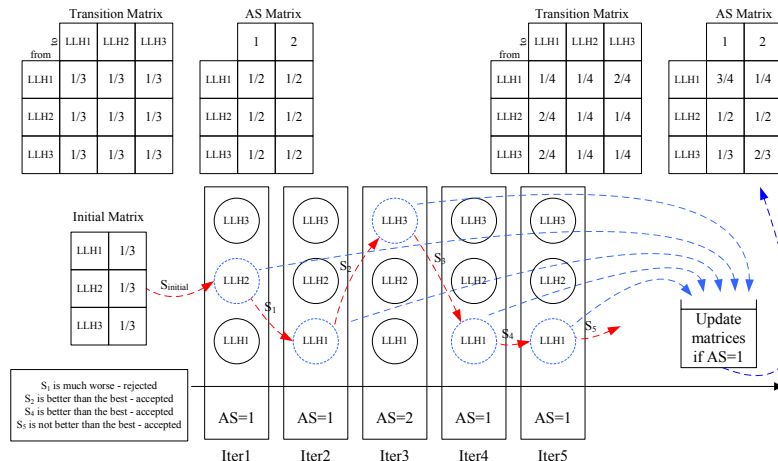
# Sequence-based Hyper-heuristic Utilising HMM



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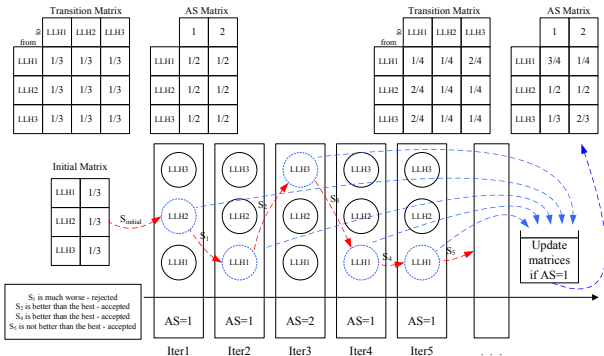
# Sequence-based Hyper-heuristic Utilising HMM



# Sequence-based Hyper-heuristic Utilising HMM

The likelihood being in state  $i$  at time  $n$ :

$$L(i, n) = L(i, n - 1) \times a_{llh_{n-1}.llh_n} \times b_{AS}$$



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## Hyper-heuristics Flexible Framework - HyFlex

Problem domain	SAT	BP	PS	PFS	TSP	VRP
no. of heuristics	11	8	12	15	13	10
mutational	0-5	0,3,5	11	0-4	0-4	0,1,7
ruin & re-create	6	1,2	5-7	5,6	5	2,3
hill climbing	7,8	4,6	0-4	7-10	6-8	4,8,9
crossover	9,10	7	8-10	11-14	9-12	5,6

Each heuristic is associated with a problem and heuristic dependent parameter. We discretised the choices into 11 different parameters (P).

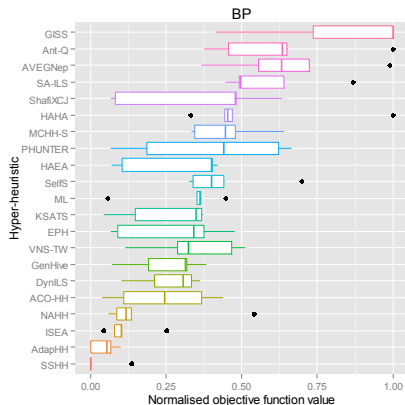
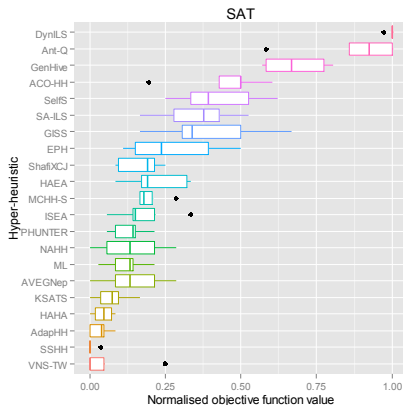
Gabriela Ochoa, Matthew Hyde, Tim Curtois, Jose A. Vazquez-Rodriguez, James Walker, Michel Gendreau, Graham Kendall, Barry McCollum, Andrew J. Parkes, Sanja Petrovic and Edmund K. Burke HyFlex: a benchmark framework for cross-domain heuristic search. In J.-K. Hao and M. Middendorf, editors, *Evolutionary Computation in Combinatorial Optimization*, volume 7245 of *Lecture Notes in Computer Science*, pages 136-147. Springer Berlin Heidelberg, 2012.

# Hyper-heuristics Flexible Framework - HyFlex

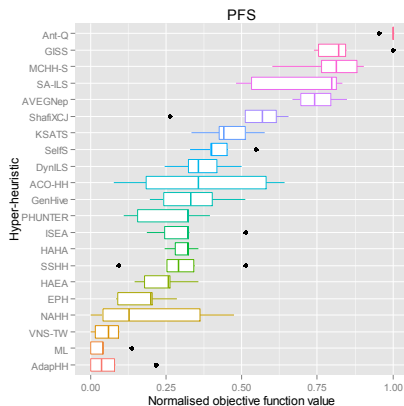
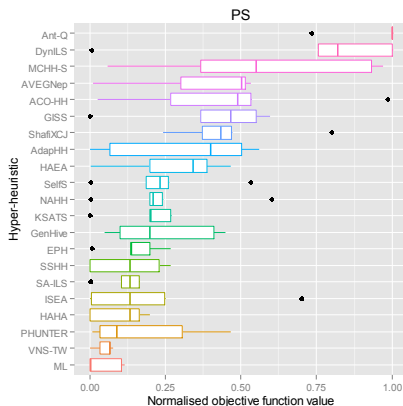
SSHH and Cross-domain Heuristic Search Challenge (CHeSC 2011)  
 competing algorithms (Formula-1 scoring system).

Method	SAT	BP	PS	PFS	TSP	VRP	Overall
<b>SSHH</b>	<b>39.10</b>	<b>45.00</b>	<b>22.50</b>	<b>3.50</b>	<b>41.00</b>	<b>14.00</b>	<b>165.10</b>
AdapHH	30.43	38.00	8.00	37.00	34.75	14.00	162.18
VNS-TW	30.93	2.00	35.50	33.50	12.75	5.00	119.68
ML	10.00	8.00	29.50	39.00	10.00	21.00	117.50
PHUNTER	7.00	2.00	11.50	8.00	22.75	32.00	83.25
EPH	0.00	6.00	9.00	21.00	29.75	11.00	76.75
HAHA	26.43	0.00	23.00	3.50	0.00	13.00	65.93
NAHH	10.50	15.00	1.00	22.00	10.00	6.00	64.50
KSATS-HH	20.35	9.00	7.00	0.00	0.00	21.00	57.35
ISEA	3.50	23.00	14.50	3.50	7.00	3.00	54.50
HAEA	0.00	1.00	1.00	8.00	8.00	25.00	43.00
ACO-HH	0.00	16.00	0.00	9.00	7.00	1.00	33.00
GenHive	0.00	10.00	6.50	7.00	2.00	6.00	31.50
SA-ILS	0.25	0.00	16.00	0.00	0.00	4.00	20.25
XCJ	3.50	11.00	0.00	0.00	0.00	5.00	19.50
AVEG-Nep	9.50	0.00	0.00	0.00	0.00	8.00	17.50
DynILS	0.00	9.00	0.00	0.00	8.00	0.00	17.00
GISS	0.25	0.00	8.00	0.00	0.00	6.00	14.25
SelfSearch	0.00	0.00	2.00	0.00	2.00	0.00	4.00
MCHH-S	3.25	0.00	0.00	0.00	0.00	0.00	3.25
Ant-Q	0.00	0.00	0.00	0.00	0.00	0.00	0.00

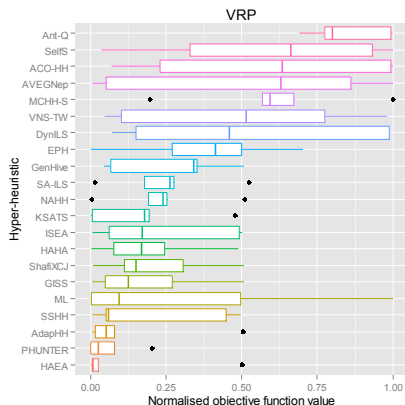
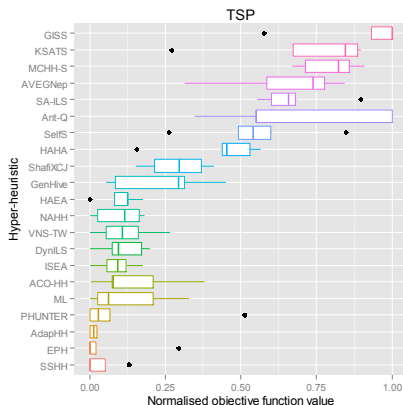
# Hyper-heuristics Flexible Framework - HyFlex (Boxplots)



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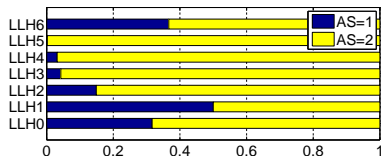


# Hyper-heuristics Flexible Framework - HyFlex (Boxplots)

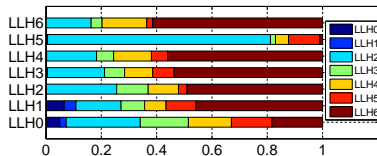


# Hyper-heuristics Flexible Framework - HyFlex (BP)

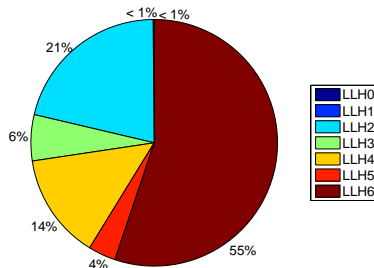
Acceptance Strategy



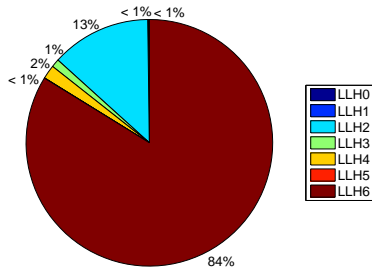
Next Low Level Heuristic



Utilisation Rate (ALL)

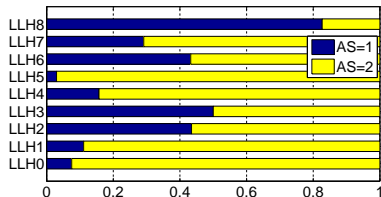


Utilisation Rate (AS=1)

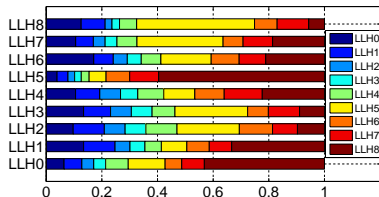


# Hyper-heuristics Flexible Framework - HyFlex (TSP)

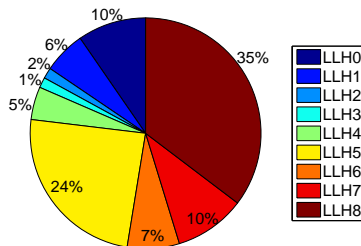
Acceptance Strategy



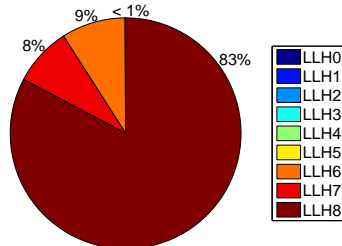
Next Low Level Heuristic



Utilisation Rate (ALL)



Utilisation Rate (AS=1)



# High School Timetabling Problem

At time of submission:

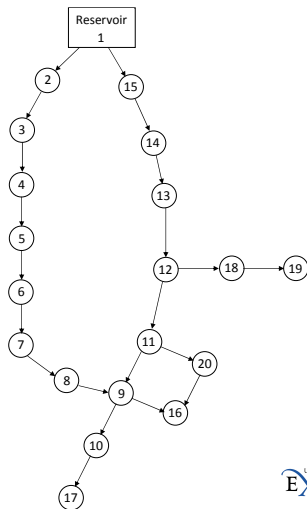
Instance	SSHH	Best known	Instance	SSHH	Best known
Australia-BGHS98	<b>0.520</b>	1.386	Greece-HighSchool1	<b>0.0</b>	<b>0.0</b>
Australia-SAHS96	<b>0.2</b>	0.24	Greece-ThirdHighSchool2010	<b>0.0</b>	<b>0.0</b>
Australia-TE599	<b>0.61</b>	0.125	Greece-WesternUniversity4	<b>0.4</b>	<b>0.4</b>
Brazil-Instance2	0.10	<b>0.5</b>	Italy-Instance4	0.38	<b>0.34</b>
Brazil-Instance4	2.117	<b>0.51</b>	Kosova-Instance1	<b>0.3</b>	<b>0.3</b>
Brazil-Instance6	0.101	<b>0.35</b>	Netherlands-Kottenpark2003	<b>0.466</b>	0.617
Denmark-Falkonergaardens2012	<b>0.1522</b>	0.3310	Netherlands-Kottenpark2005	<b>0.811</b>	0.1078
Denmark-HasserisGymnasium2012	<b>12.2628</b>	12.3124	Netherlands-Kottenpark2009	2.7495	<b>0.9180</b>
Denmark-VejenGymnasium2009	<b>2.2731</b>	2.4097	England-StPaul	19.1294	<b>16.2258</b>
Spain-School	0.517	<b>0.336</b>	USA-Westside2009	<b>0.512</b>	0.697
Finland-College	0.8	<b>0.0</b>	South Africa-Lewitt2009	0.52	<b>0.0</b>
Finland-HighSchool	0.7	<b>0.1</b>	South Africa-Woodlands2009	9.0	<b>0.0</b>
Finland-SecondarySchool	0.89	<b>0.83</b>			

**Ahmed Kheiri and Ed Keedwell** A sequence-based selection hyper-heuristic for operational research problems with a case study in high school timetabling problems. Information Sciences, in preparation.



# New York Tunnels Water Distribution Network

Algorithm	Best Solution Cost	Evaluations
SSHH	38.64m	24,996
CGA	38.64m	44,324
SGA	38.64m	54,789
SDE	38.64m	12,855
DDE	38.64m	13,214



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## Features of the Algorithm

- ▶ The selection method is parameter-free.
- ▶ It is capable of discovering sequences of heuristics of any size.
- ▶ It discovers automatically when to move from intensification to diversification and vice versa.
- ▶ The HMM matrices can be analysed to determine what has been learned about the search space and relationships between low level heuristics and acceptance strategy.
- ▶ The sequence-based acceptance strategy allows exploration and exploitation of the heuristic space.

# Thank You