Hyper-heuristics and Cross-domain Optimisation

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Outline

- 1. Hyper-heuristics (for optimisation)
 - Search and optimisation in practice
 - The need for automation
 - Motivation, definition, origins, classification
- **2.** Case studies
 - The HyFlex framework and the cross-domain challenge
 - Hyper-heuristics for the course timetabling problem
- **3.** Discussion
 - Contributions/ Collaborations DAASE
 - Research vision







Search and optimisation in practice

Many challenging applications in science and industry can be formulated as optimisation problems!



Problem Model

- Problem representation
- Constraints
- A fitness function

Optimisation/Search Algorithm

- Exact methods
- Approximate (heuristic) methods

Solution to the Model

- Feasible candidate solution
- Optimal (or good enough) value of the objective function

Algorithm selection, configuration and tuning

Holy-Grail: Finding the most suitable optimisation/search algorithm and its correct setting for solving a given problem





Can we automate these processes?

Autonomous/adaptive (self-*) search approaches

• Incorporate ideas from machine learning and statistics

Static (Offline) Configuration

- Algorithm selection
- Algorithm portfolios
- Algorithm configuration
- Parameter tuning
- Hyper-heuristics



Dynamic (Online) Control

- Adaptive operator selection
- Parameter control
- Reactive search
- Adaptive memetic algorithms
- Hyper-heuristics



Hyper-heuristics: Motivation

- Decision support systems that are off the peg vs. Taylor made
- Work well on different problems
- How general we could make hyper-heuristics ?
 (*no free lunch* theorem)

Thanks to Prof. E. K. Burke and Dr. Rong Qu, For this an the next Slide



What is a hyper-heuristic?



Hyper-heuristics:

"Operate on a search space of heuristics"







Joint work with: E. K. Burke, M. Hyde, T. Curtois, J. Walker M. Gendreau, J. A Vazquez-Rodriguez,

Case Study 1: Selection (dynamic) hyper-heuristics

- The HyFlex software framework
- The vehicle routing problem
- The Cross-domain 'Decathlon' competition





The concept of **HyFlex**

Hyper-heuristics **Problem Domains** (general-purpose) (problem-specific) **Adap**HH Pers. Sched. **VNS-**TW VRP **HyFlex** Others ... Others Software Interface ...

Vehicle routing domain



Mutational	Local Search	Ruin & Recreate	Crossover
Two-opt [4] Or-opt [5] Two-opt* [2]	Simple hill- climbers based on	Time-based radial ruin[6]	Combine routes
Shift [1] Interchange [1]	mutational heuristics GENI [3]	Location-based radial ruin[6]	orders routes according to length

[1] M. W. P. Savelsbergh. The vehicle routing problem with time windows: Minimizing route duration. *INFORMS Journal on Computing*, *4*(2):146-154, 1992.

[2] J-Y. Potvin and J-M. Rousseau. An exchange heuristic for routing problems with time windows. *The Journal of the Operational Research Society*, 1995.

[3] M. Gendreau, A. Hertz, and G. Laporte. A new insertion and postoptimization procedures for the traveling salesman problem. *Operations Research*, *1992*.

[4] O. Braysy and M. Gendreau. Vehicle routing problem with time windows, part i: Route construction and local search algorithms. *Transportation Science*, 2005.

[5] I. Or. Traveling salesman-type combinatorial problems and their relation to the logistics of regional blood banking. *PhD thesis, Northwestern*

[6] G. Schrimpf, J. Schneider, H. Stamm-Wilbrandt, and G. Dueck. Record breaking optimization results using the ruin and recreate principle. *Journal of Computational Physics*, 2000.



The Competition



Reg. participants: 43 (23 countries), **Competition entries**: 20 (14 countries) **Page visits** (since May 2011): Total visits: 5,470, Total page views: 10,929



Results – Top 5: Formula 1 score







Case Study 2: Hyper-heuristics for the Course Timetabling Problem

- The course timetabling problem
- Search operators
- Results

Joint work with Jorge A. Soria (PhD Student, University of Leon, Mexico) Jerry Swan, Edmund K. Burke

Course timetabling problem

Assigns subjects to individual students

Events (courses of subjects)	• $E = \{e_1, e_2,, e_n\}$
Time periods	• $T = \{t_1, t_2, t_s\}$
Places (classrooms)	• $P = \{p_1, p_2, p_s\}$
Students	• $A = \{a_1, a_2, a_s\}$
Assignment	• quadruple (<i>e</i> , <i>t</i> , <i>p</i> , <i>S</i>) <i>S</i> subset A
Timetabling solution	• complete set of <i>n</i> assignments, that satisfies the constraints

Representation: set of integers representing indexes



Fitness function: $min(FA) = \sum_{i=1}^{|V|} FA_{V_i}$

$$FA_{V_i} = \sum_{s=1}^{|V_i|} \sum_{l=s+1}^{|V_i|} (S(s) \cap S(l))$$

Instances: real-world, ITC 2002, 2007

The pool of operators

Simple Random Perturbation (SRP)

Best Single Perturbation (BSP)

Statistical Dynamic Perturbation (SDP)

Double Dynamic Perturbation (DDP)

Swap (SWP)

Two Points Perturbation (2PP)

Move to Less Conflict (MLC)

Burke-Abdhulla (BA)

Conant-Pablos (LSA)

QUESTION: Given *K* search operators

- How to select (on the fly) the operator to be applied next, considering the history of their performance?
- Measuring performance → Assigning credit → Selecting the operator: Fitness Improvement + Extreme Credit + Adaptive Pursuit

Competitive results and 3 new best-known solutions!

Table 6: Comparative Best Soft Constraint Results ITC2007 (In all cases Hard Constraints are 0)

;	Atsuna	Cambazard	Chiarandini	Nothegger	Muller	ExAOSAP
ITC2007-3	382	164	288	391	272	290
ITC2007-4	529	310	385	$\boldsymbol{239}$	425	600
ITC2007-7	0	6	10	0	13	30
ITC2007-8	0	0	0	4	6	0
ITC2007-11	548	$\boldsymbol{178}$	240	547	253	350
ITC2007-15	379	0	0	0	5	0
ITC2007-16	191	2	1	41	132	0
ITC2007-17	1	0	5	68	72	0
ITC2007-20	1215	445	596	Х	878	150
ITC2007-21	0	0	602	33	40	0
ITC2007-24	720	21	822	30	372	0

Frequency of selection of the operators, *HHRand*



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SDP TSSRP DDP BS P

Frequency of selection of the operators, *HHExAP*



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Contributions/Collaborations with DAASE partners

Good algorithms are Hybrid and Dynamic!

- Adaptive approaches can beat state-of-the-art domain specific algorithms
- They are more robust and general

New metrics for impact/ New credit assignment mechanisms

- Multiobjective impact/credit
- Considering noisy/costly evaluations:
- Online learning: concept drift, ensembles:Adaptive mechanisms from filter theory (multinomial tracking)

New problems

- SBSE Domains: Requirements, Testing, Improving and Repair
- Industrial applications (DAASE industrial partners)