Adaptive Operator Selection at the Hyper-Level

Eduardo Krempser[1], **Álvaro Fialho**[2], **Helio J. C. Barbosa**[1]

[1]Laboratório Nacional de Computação Científica, Petrópolis, Brazil

[2]Nokia Institute of Technology (INdT), Manaus, Brazil

krempser@lncc.br, alvaro.fialho@indt.org.br, hcbm@lncc.br

ABSTRACT

Whenever a new problem needs to be tackled, one needs to decide which of the many existing metaheuristics would be the most adequate one; but it is very difficult to know their performance a priori. And then, when a metaheuristic is chosen, there are still its parameters that need to be set by the user. This parameter setting is usually very problem-dependent, significantly affecting their performance. In this work we propose the use of an Adaptive Operator Selection (AOS) mechanism to automatically control, while solving the problem, (i) which metaheuristic to use for the generation of a new solution, (here a Genetic Algorithm (GA) and a Differential Evolution (DE) scheme); and (ii) which corresponding operator should be used. Two AOS schemes are considered: the Adaptive Pursuit and the Fitness Area Under Curve Multi-Armed Bandit. The resulting algorithm, named as Adaptive Hyper-Heuristic (HH), is evaluated on the BBOB noiseless testbed, showing superior performance when compared to (a) the same HH without adaptation, and also (b) the adaptive DE and GA.

1. INTRODUCTION

- Metaheuristics have been used to solve a wide range of complex optimization problems
- Many different metaheuristics can be found in the literature
- Each of them presenting its own specifications, resulting into different behaviors of the search process
- When a metaheuristic is chosen, there are still its parameters that need to be set by the user
- This parameter setting is usually very problem-dependent, significantly affecting their performance
- In this work we propose the use of an Adaptive Operator Selection (AOS)[1] mechanism to automatically control:
  - which metaheuristic to use for the generation of a new solution, exemplified here by a Genetic Algorithm (GA) and a Differential Evolution (DE)
  - which corresponding operator should be used
- Two AOS schemes are considered: the Adaptive Pursuit[3] and the Fitness Area Under Curve Multi-Armed Bandit[2]
- The resulting algorithm, named as Adaptive Hyper-Heuristic (HH), is evaluated on the BBOB noiseless testbed[4]

2. ADAPTIVE OPERATOR SELECTION

- The Adaptive Operator Selection aims to adjust the application of operators while the search process is performed and two aspects were defined:
  - how to measure the performance of the operators (Credit Assignment)
  - how to select among them after these performance measurements are made (Operator Selection)
- We consider two existing schemes from the literature:
  - Adaptive Pursuit (AP), combinated with the Extreme Credit Assignment
  - Fitness-based Area-Under-Curve - Bandit (AUC), a fully comparison-based adaptive operator selection was recently proposed[2], which its Credit Assignment scheme is based on the ranks of the fitness improvements, and not on their raw values

3. ADAPTIVE HYPER-HEURISTIC

- The adaptive proposed algorithm combines the GA and DE:
  - choosing which metaheuristic and operators should be used
  - each new individual is generated by selected metaheuristic
- The DE replacement mechanism is applied
- The algorithms and operators are chosen by AOS methods
- The impact measure is defined by the improvement in fitness

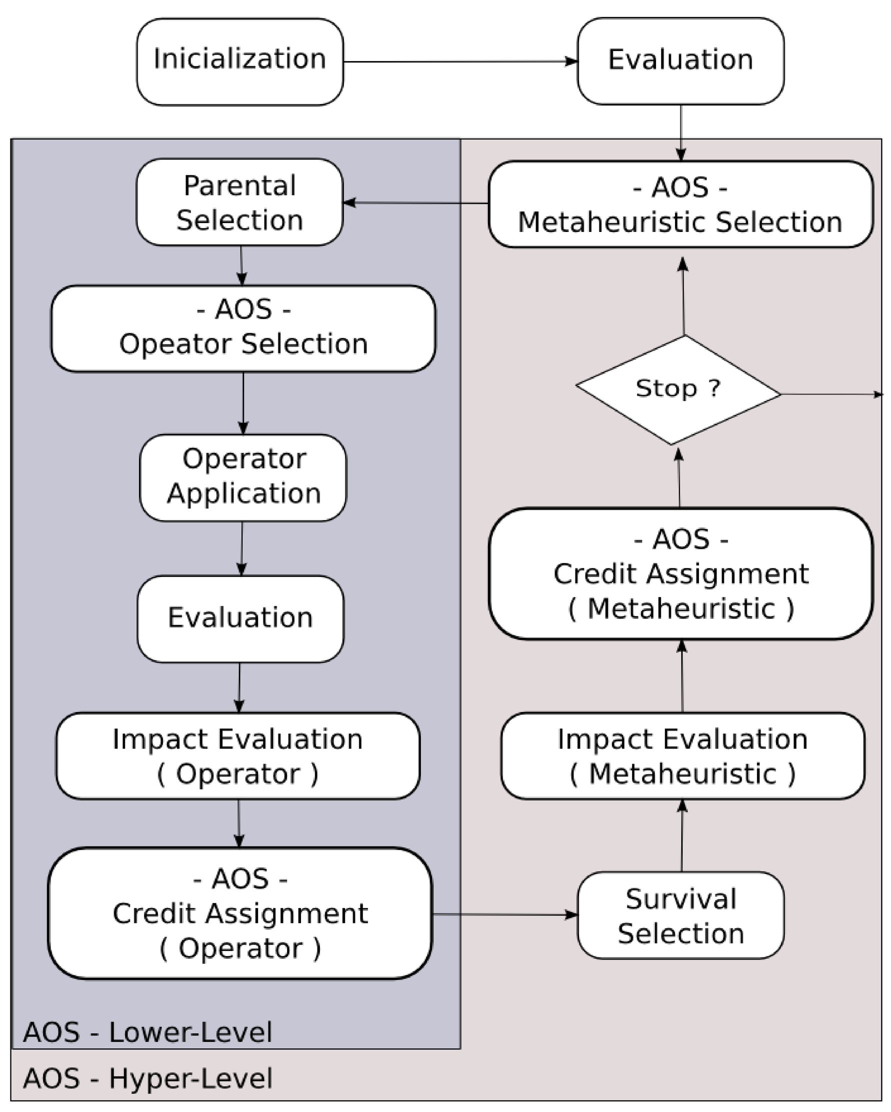

Figure 1: *HH-AOS scheme.*

4. METAHEURISTICS AND OPERATORS

- The metaheuristics and its operators considered in our numerical experiments:
  - Differential Evolution
    - **DE/rand/2/bin:** $u_{j,i} = x_{j,r_1} + F(x_{j,r_2} - x_{j,r_3}) + F(x_{j,r_4} - x_{j,r_5})$
    - **DE/rand-to-best/2/bin:** $u_{j,i} = x_{j,r_1} + F(x_{j,best} - x_{j,r_1}) + F(x_{j,r_2} - x_{j,r_3}) + F(x_{j,r_4} - x_{j,r_5})$
    - **DE/current-to-rand/1/bin:** $u_{j,i} = x_{j,i} + F(x_{j,r_1} - x_{j,r_i}) + F(x_{j,r_2} - x_{j,r_3})$
  - Genetic Algorithm
    - The one-point crossover operator
    - The Uniform crossover
    - The blend crossover operator (BLX-α)
    - A simple mutation operator (increments each variable)
    - The non-uniform mutation operator
- Other heuristics as well as more than two could have been used

5. COMPARATIVE RESULTS

- Experiments were conducted using the BBOB noiseless testbed
  - 24 single-objective functions from 5 different classes
- Our proposal – Adaptive Operator Selection at the Hyper-Heuristic (HH), was compared with each algorithm individually with:
  - uniform selection (Naive)
  - the adaptive pursuit selection (AP)
  - the fitness area under curve bandit selection (AUC)

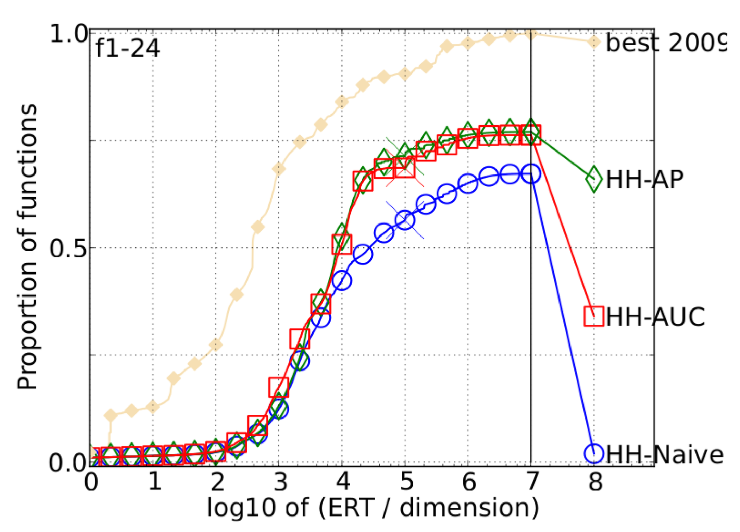

Figure 2: *Empirical cumulative distribution of the bootstrapped distribution of ERT over dimension for 50 targets in $10^{[-8..2]}$ for all functions to HH*

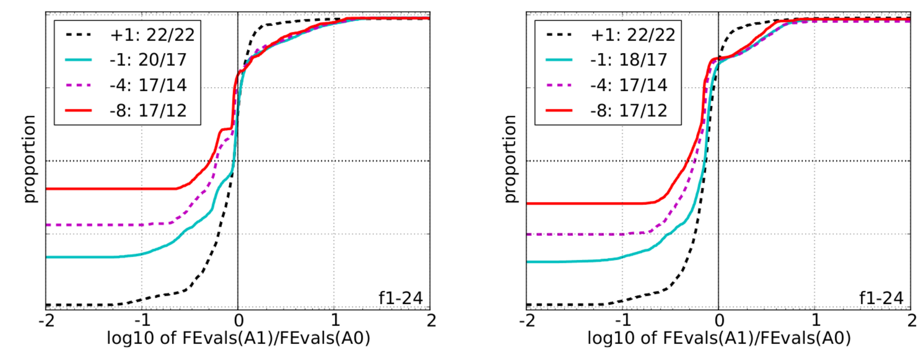

Figure 3: *Empirical cumulative distributions (ECDF) speed-up ratios in 20-D to HH. ECDF of FEval ratios of Adaptive Pursuit (AP) and AUC-Bandit (AUC) divided by Naive, all trial pairs for each function. (AP/AUC first)*

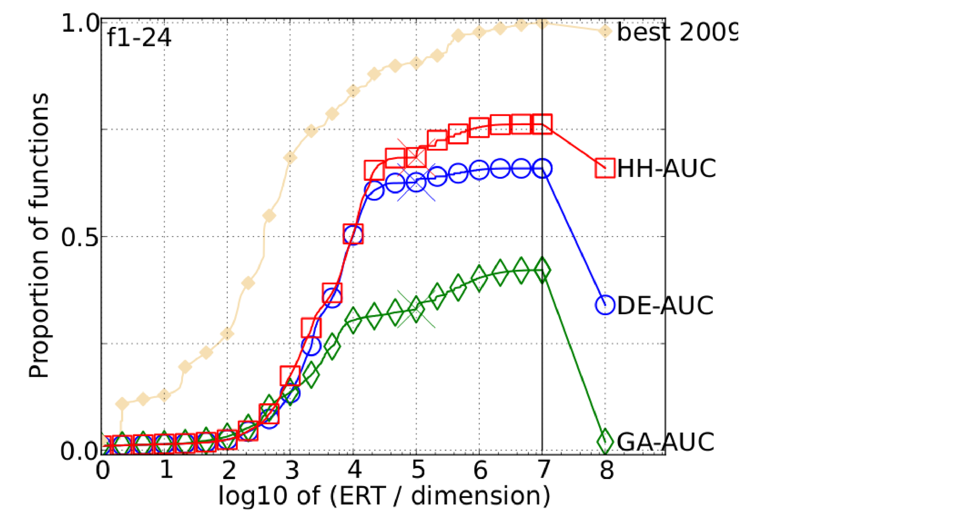

Figure 4: *Empirical cumulative distribution of the bootstrapped distribution of ERT over dimension for 50 targets in $10^{[-8..2]}$ for all functions to DE, GA and HH, all using the AUC adaptive operator selection.*

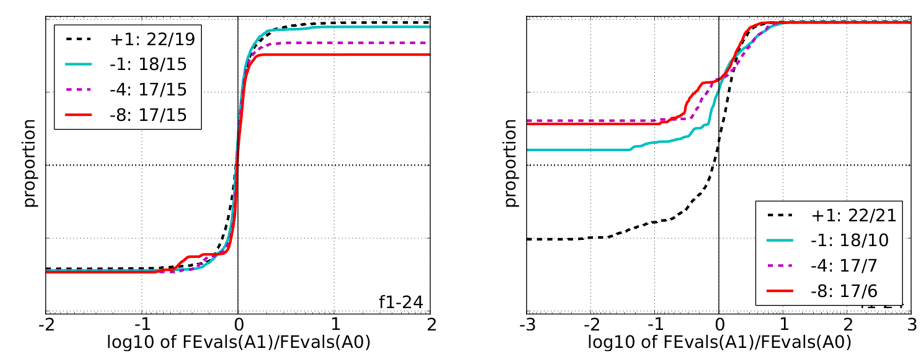

Figure 5: *Empirical cumulative distributions (ECDF) speed-up ratios in 20-D to DE-AUC, GA-AUC and HH-AUC. ECDF of FEval ratios of HH-AUC respectively divided by DE-AUC and GA-AUC, all trial pairs for each function. (HH-AUC first)*

6. CONCLUSIONS

- Our proposal employs three independent instances of the recent Fitness Area Under Curve Multi-Armed Bandit AOS algorithm:
  - one instance controlling the choices at the Hyper-level, and
  - the other selecting between the operators for the DE and GA
- It showed superior performance when compared to:
  - the same Hyper-Heuristic without adaptive behavior
  - the single-heuristic counterparts
- These results empirically confirm that the AOS at the Hyper-level is efficient, and that the intelligent switching between different metaheuristics is a path worth to be further investigated

REFERENCES

[1] Á. Fialho. Adaptive Operator Selection for Optimization. PhD Tesis: Université Paris-Sud XI, 2010, Orsay, France.

[2] Á. Fialho, M. Schoenauer, M. Sebag. Toward comparison-based adaptive operator selection. In: Proc. GECCO (2010).

[3] D. Thierens An adaptive pursuit strategy for allocating operator probabilities. In: Proc. GECCO (2005).

[4] N. Hansen, A. Auger, S. Finck, R. Ros. Real-parameter black-box optimization benchmarking: Noiseless functions definitions. Tech. rep., RR-6829, INRIA (2009).

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