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Solving real-world multi-objective engineering optimization problems with an Election-Based Hyper-Heuristic

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OptMAS 2018, Stockholm, Sweden

July 14th, 2018

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Evolutionary algorithms

- Evolutionary algorithms are algorithms which employ Darwin's theory of the survival of the fittest as their inspiration.
- They keep a population of solutions and generate new solutions using crossover and mutation operators;
- They needs a fitness function specification which tells how good is a solution;
- They are used to solve problems when there is not any problem-specific algorithm that gives a satisfactory solution in reasonable time.

Evolutionary algorithms - objective

Algorithm 1: Generic Evolutionary Algorithm

```
begin
    Initialize the population with random solutions;
    Evaluate solutions according to the objective function;
    while a termination condition is not satisfied do
        Select parents;
        Recombine pairs of parents;
        Mutate the resulting offspring;
        Evaluate new solutions according to the objective function;
        Select solutions to compose the next generation;
    end
end
```

Evolutionary algorithms - objective

Evolutionary algorithms can be classified according to their number of objectives (number of fitness functions) as mono-objective and multi-objective algorithms.

- Mono-objective evolutionary algorithms:
  - Genetic Algorithm (GA) [4]
- Multi-objective evolutionary algorithms (MOEA):
  - Non-Dominated Sorting Genetic Algorithm II (NSGA-II) [3]
  - Strength Pareto Evolutionary Algorithm 2 (SPEA2) [11]
  - Indicator-Based Evolutionary Algorithm (IBEA) [10]
  - Generalized Differential Evolution (GDE3) [7]

Quality Indicators in Multi-objective Optimization

There are several quality indicators to tell us how good algorithms outcomes are:

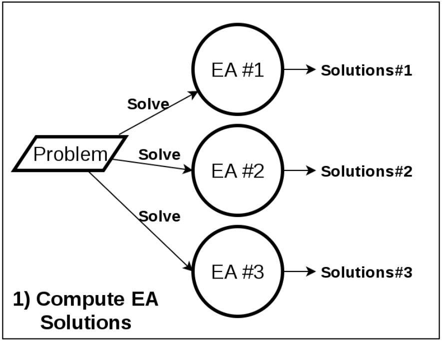
- Hypervolume;
- Ratio of non-dominated solutions;
- Hyper-area Ratio;
- Pareto Dominance Indicator;
- Uniform distribution of non-dominated population;
- Algorithm Effort;
- Epsilon;
- General Distance;
- Inverted General Distance;

Evolutionary Algorithms - How to choose one?

Choosing an evolutionary algorithm is not a trivial task. Different evolutionary algorithms produce different results when applied to different problems. Thus to choose an Evolutionary algorithm we have to:

- Use literature recommendations OR
- Perform a tuning and choose the best algorithm considering a quality indicator.

Evolutionary Algorithms - How to choose one?



3) Compare them to find the best one

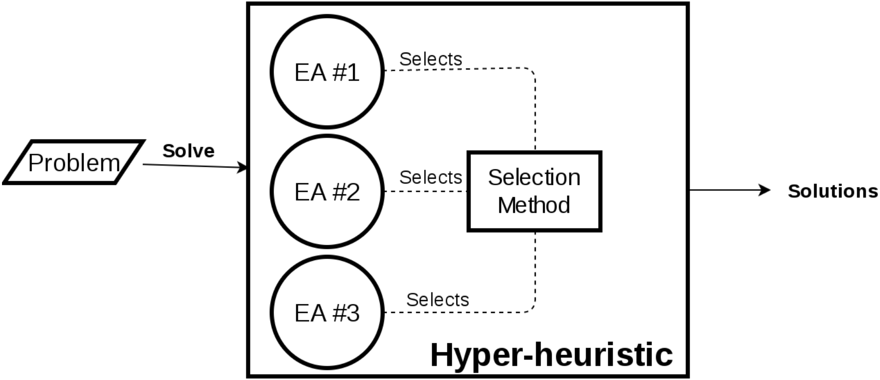
EA Results	Quality Indicator
Solutions#1	0.66
Solutions#2	0.33
Solutions#3	0.55

Evolutionary Algorithms - How to choose one?

Choosing an evolutionary algorithm is not a trivial task. Different evolutionary algorithms produce different results when applied to different problems. Thus to choose an Evolutionary algorithm we have to:

- Use literature recommendations OR
- Perform a tuning and choose the best algorithm considering a quality indicator OR
- Use a hyper-heuristic

Evolutionary algorithms - How to choose one?



Hyper-heuristic - Selection Method

Usually Hyper-heuristics employ a selection method. It can be:

- Roulette;
- A choice function;
- Multi-Armed Bandit approaches;
- Social Choice Based Approaches

MOABHH

We propose the Multi-Objective Agent-Based Hyper-Heuristic (MOABHH) [2] which has the following characteristics:

- Evolutionary algorithms (EA) as agents (*EA Agent*);
- Quality Indicators as agents (*Indicator Voters*);
- Share among *EA Agents* the number of solutions to generate;
- Allocate a bigger participation in generating new solutions to the top *EA Agents*;
- The top *EA Agents* are defined according to an election outcome, where *Indicator Voters* votes;
- We used Copeland voting method.

MOABHH - Population Sharing

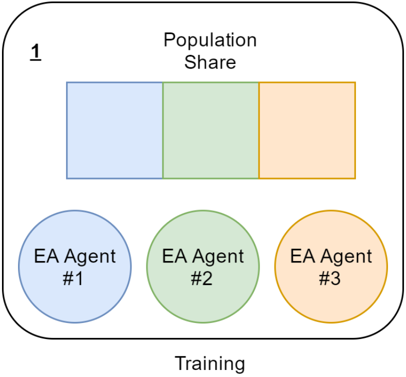


Figure 1: Population Sharing

MOABHH - Voting

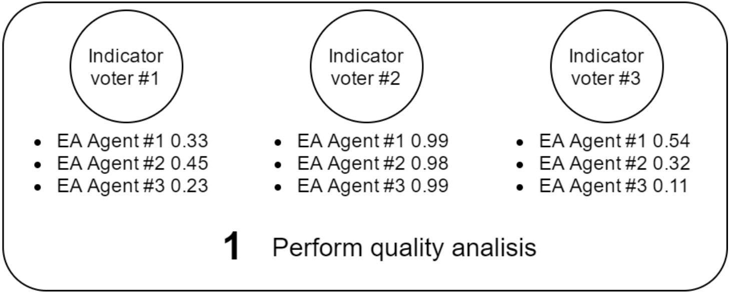


Figure 2: Voting method. First, all Indicator voter agents rank EA Agents based on their results.

MOABHH - Voting

2

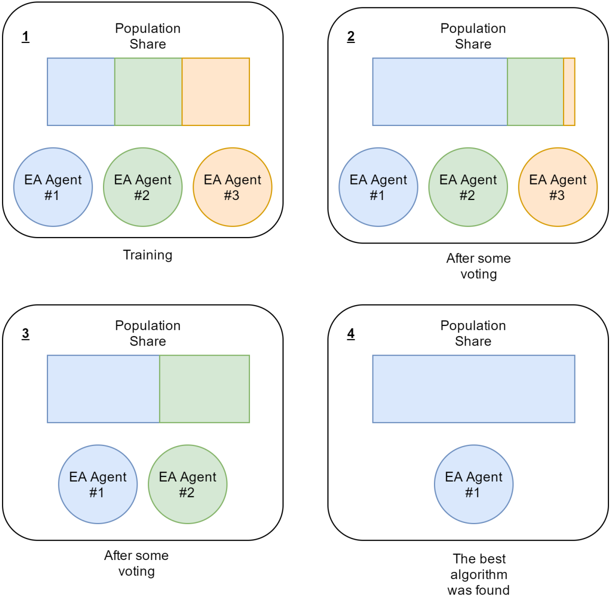
- One-on-one contest
- EA Agent#1 x EA Agent#2 on Voter #1
- EA Agent#1 x EA Agent#2 on Voter #2
- EA Agent#1 x EA Agent#2 on Voter #3
- EA Agent#1 x EA Agent#3 on Voter #1
- EA Agent#1 x EA Agent#3 on Voter #2
- EA Agent#1 x EA Agent#3 on Voter #3
- EA Agent#3 x EA Agent#2 on Voter #1
- EA Agent#3 x EA Agent#2 on Voter #2
- EA Agent#3 x EA Agent#2 on Voter #3

3

Candidate	Wins	Losses	Net	Final Rank
EA Agent#1	4	-1	3	1
EA Agent#2	3	-3	0	2
EA Agent#3	1	-4	-3	3

Figure 3: Voting method. In step 2 the Copeland voting is performed. In step 3 the Copeland ranking is generated.

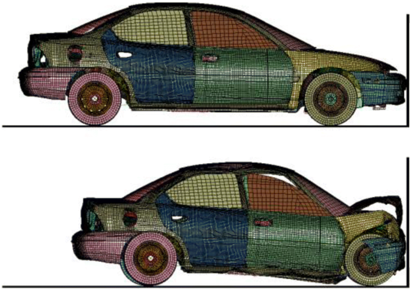
MOABHH - Population Sharing



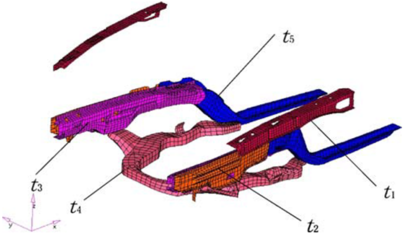
Motivations for a real-world application

- We just had performed our studies considering benchmarks:
  - WFG
  - DTLZ
  - ZDT
  - CEC09
- Pareto Front in known in advance for benchmarks. Thus we used IGD and GD as Indicator Voters;
- In real-world problems the Pareto Front is not know in advance;
- Other Indicator Voters have to be used;
- Real-world applications better propagate A.I. knowledge to other areas;

Applications: Crashworthiness



(a) A frontal crash



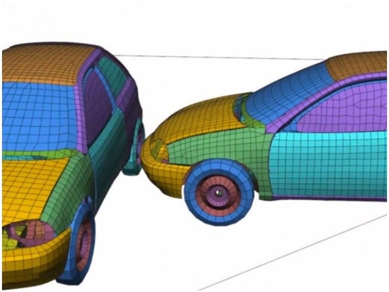
(b) Fender thickness decision variables

Figure 4: Liao et al. 2008

Problem Description:

- 3 objectives: (i) the mass, (ii) an integration of collision acceleration in the full frontal crash, (iii) the toe-board intrusion.
- 5 decision variables

Applications: Car Side Impact



Problem Description:

- 3 objectives: (i) the weight, (ii) the pubic force experienced by a passenger, (iii) the average velocity of the V-Pillar responsible for withstanding the impact load.
- 7 decision variables describing the thickness of B-Pillars, floor, cross members, door beam, roof rail, etc;
- 8 constraints.

Applications: Machining

Figure 5: A390 aluminum, widely used in automotive industry for cylinder liners and pistons etc., Source: http://www.alsi-alloys.com

Problem Description:

- 4 objectives: (i) min. the surface roughness, (ii) max. the surface integrity, (iii) max. the tool life, (iv) maximizing the metal removal rate.
- 3 decision variables Speed, feed and depth of cut;
- 3 constraints.

Applications: Water

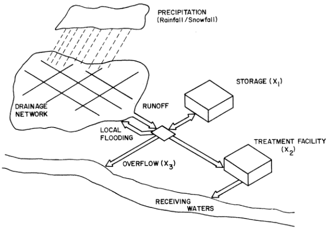


Figure 6: Musselman and Talavage, 1980

Problem Description:

- 5 objectives: (i) the drainage network cost, (ii) the storage facility cost, (iii) the treatment facility cost, (iv) the expected flood damage cost, and (v) the expected economic loss due to flood.
- 3 decision variables: storage capacity, the maximum treatment rate and the maximum allowable overflow rate;
- 7 constraints.

Experiments - Configuration

- 4 algorithms (candidates):
  - IBEA;
  - SPEA2;
  - NSGA-II;
  - GDE3.
- 6 Quality indicators (voters):
  - Hypervolume;
  - Ratio of non-dominated solutions;
  - Hyper-area Ratio;
  - Pareto Dominance Indicator;
  - Uniform distribution of non-dominated population;
  - Algorithm Effort.
- 40 independent runs.
- Kruskal-Wallis test with 1% of significance level.

Results

Table 1: Hypervolume, IGD and Epsilon Result Table

	Problem	GDE3	IBEA	NSGAII	SPEA2	MOABHH
Hyp.	Car Side Impact	4.4342E-01	**4.7710E-01**	3.7671E-01	4.4507E-01	**4.7161E-01**
	CrashWorthiness	**7.3603E-01**	7.0594E-01	6.6108E-01	7.2210E-01	**7.3985E-01**
	Water	5.6227E-01	5.0439E-01	4.3440E-01	4.9700E-01	**5.8632E-01**
	Machining	1.8393E-01	**2.7348E-01**	1.7288E-01	1.7705E-01	**2.7118E-01**
IGD	Car Side Impact	7.8878E-04	8.1957E-04	1.2878E-03	7.5318E-04	**6.6803E-04**
	Crash Worthiness	**6.9652E-04**	2.6247E-03	1.2639E-03	7.5822E-04	**4.2570E-04**
	Water	1.4869E-03	3.5247E-03	2.1495E-03	1.9045E-03	**8.9055E-04**
	Machining	1.6902E-03	**5.1369E-04**	1.6953E-03	1.7521E-03	**5.0530E-04**
Ep.	Car Side Impact	**1.6403E-01**	9.6482E-02	1.9015E-01	1.8226E-01	1.3509E-01
	Crash Worthiness	**5.3299E-02**	1.4667E-01	1.1723E-01	6.4985E-02	**4.3900E-02**
	Water	**1.4684E-01**	2.5247E-01	2.5750E-01	2.1015E-01	**1.1912E-01**
	Machining	4.8167E-01	**1.6378E-01**	4.9150E-01	5.0770E-01	**1.9654E-01**

Conclusions

- MOABHH was very competitive against the MOEAs;
- Most of the cases, it has found better Hypervolume, IGD and Epsilon averages;
- Sometimes with statistical difference;
- We believe that this makes this approach interesting for engineers to solve their real-world problems.

Future work

- Use different meta-heuristic, such as MOEA/D-DRA [9], MOEA/D-DD [8] and MOMBI-II [5];
- Use different voting methods, such as Kemeny [6] and Borda [1];
- Solve up to ten objectives problems.

Acknowledgments

CNPq

Thank you!

MOABHH - Pseudocode

Algorithm 2: MOABHH Pseudocode.

```
Input: Problem, MOABHH params
begin
    Initialize agents and artifacts;
    Generate a random population of solutions;
    while Training do
        Uniformly share the population among EA Agents;
        EA Agents execute for one generation;
        Update the main population;
    end
    while Executing do
        Evaluate EA Agents qualities;
        Perform the voting method;
        Share population among EA Agents according to voting results;
        EA Agents execute for γ generations;
        Update the main population;
    end
    return Main population
end
```

Where $\gamma = 12$

HH Assign

$$fx(pos, n) = \left\{ \begin{array}{l} 2^n \text{ if } pos = 1 \\ 0 \text{ if } pos = n \\ 2^{n-pos} \text{ otherwise} \end{array} \right\} \tag{1}$$

$$\forall pos \in rank \frac{fx(pos, n)}{\sum_{i=1}^{n} fx(i, n)} * \beta \tag{2}$$

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