Some Applications of Evolutionary Algorithms

TIES451 Selected Topics in Soft Computing

JYVÄSKYLÄN YLIOPISTO
UNIVERSITY OF JYVÄSKYLÄ

Agenda

- Applications of single-objective EAs
  - How does it work?
  - Some example applications of the EAs we studied
- Applications of multiobjective EAs
  - How does it work?
  - Some example applications
- Useful links

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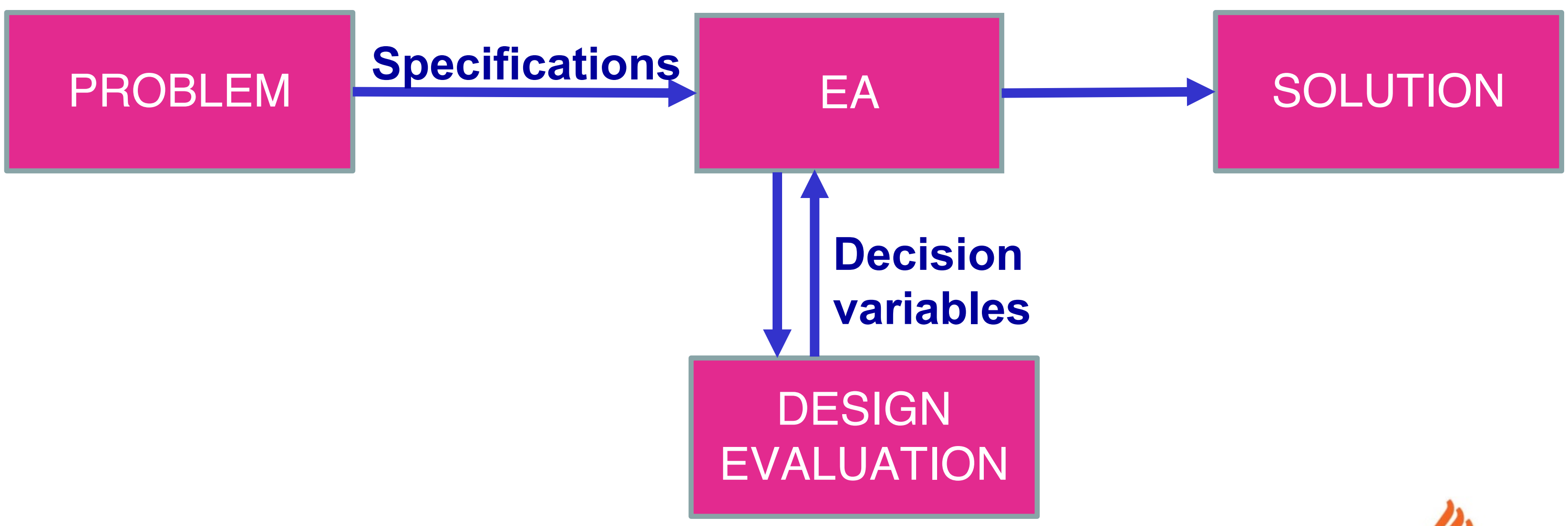
UNIVERSITY OF JYVÄSKYLÄ

Applications of single-objective EAs

Workflow

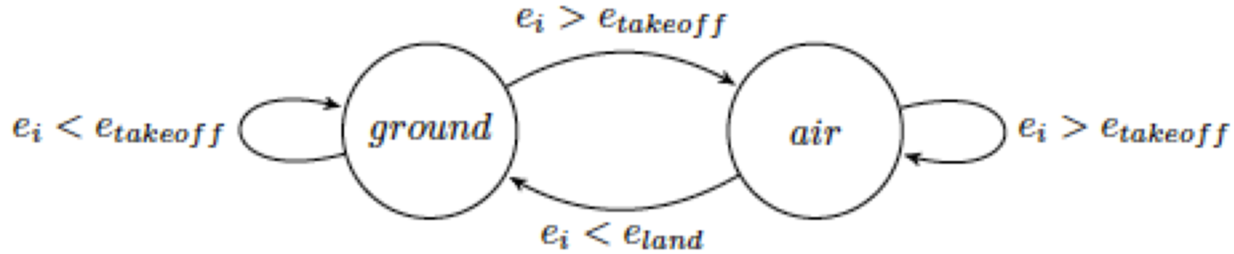

PROBLEM
Specifications
EA
SOLUTION
Decision
variables
DESIGN
EVALUATION

Energy aware swarm robots

- Swarm robotics: swarm collectively learn about a pre-defined task
- Aerial robots consider both movements and energy levels
- Each individual makes own decisions:
  - estimate the amount of required energy for moving to the next position,
  - considering the trade-off between profit and energy consumption

S. Mostaghim, C. Steup, F. Witt. Energy Aware Particle Swarm Optimization as Search Mechanism for Aerial Micro-robots. *In proceedings of IEEE Swarm Intelligence Symposium, IEEE SSCI* 2016.

Movement model



Energy aware PSO

Input : N Individuals
t = 0
Initialize the individuals
for $i = 1$ *to* N **do**
    $\vec{x}_i(t)$ = StartPosition(S)
    $\vec{v}_i(t)$ = 0
    $e_i(t)$ = Random(e_{min}, e_{max})
end
while *Stopping Criterion not fulfilled* **do**
    for $i = 1$ *to* N **do**
        $state_i(t)$ = DecideState($\vec{x}_i(t)$, $e_i(t)$)
        if $state_i(t)$ == *Ground* **then**
            charge: $e_i(t) = e_i(t) + c$
        end
        else
            $\vec{x}_g(t)$ = LeaderSelection($state_i(t)$, $e_i(t)$)
            $\vec{v}_i(t+1)$ = ComputeVelocity ($\vec{x}_i(t)$, $\vec{x}_g(t)$)
            $\vec{x}_i(t+1)$ = UpdatePosition($\vec{v}_i(t)$, $\vec{x}_i(t)$)
            $e_i(t+1)$ = ComputeEnergy($\vec{v}_i(t+1)$)
        end
    end
    $t = t + 1$
end

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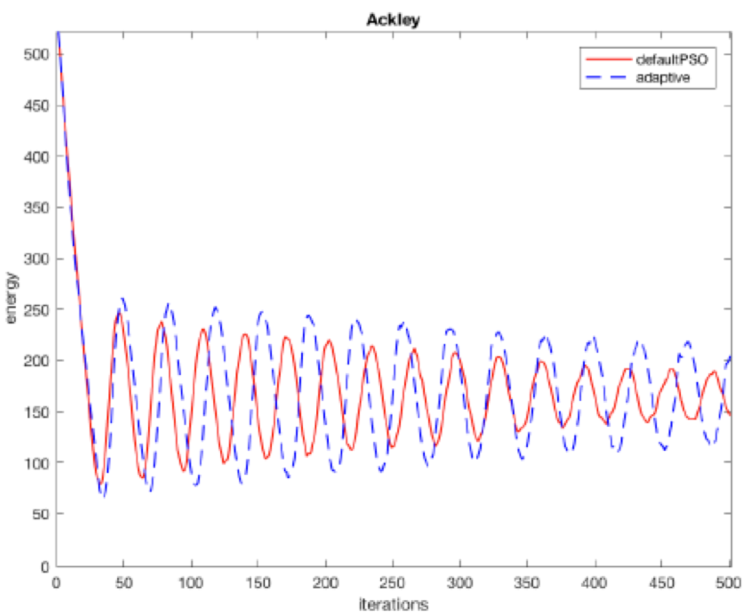
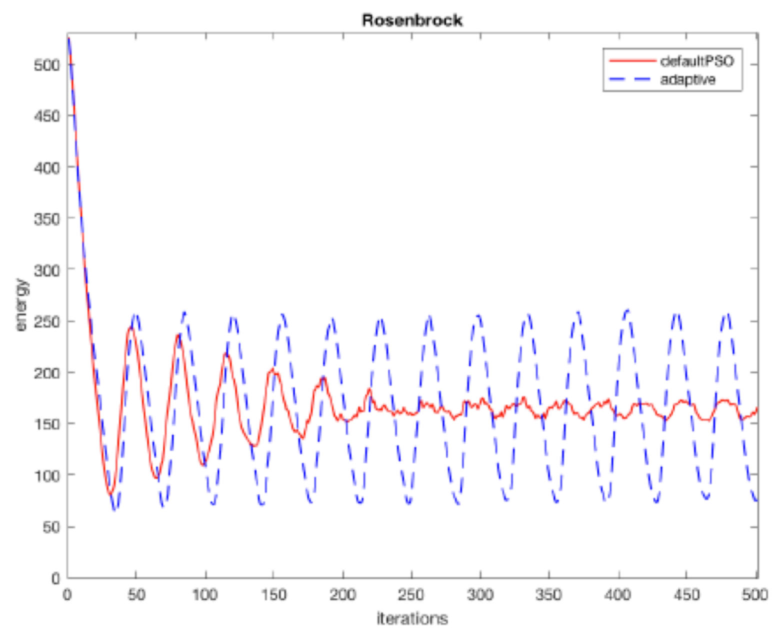
Total amount of available energy in the swarm. Both method has a cycle energy level

EAPSO requires less recharging circle

Robots charge at the basin





Evaluation function of chess program with DE

- Decision variables: the weights in different parts of the evaluation function
- Apply genetic operators to get a new set of individuals Pu
- Each individual of the current population plays the game with N randomly chosen individuals in Pu and collect points.
- Combine both population and selected based on the points gained.

B. Boskovic, S. Greiner, J. Brest and V. Zumer, A Differential Evolution for the Tuning of a Chess Evaluation Function, *2006 IEEE International Conference on Evolutionary Computation*,, 2006, pp. 1851-1856.

$$eval = X_m(M_{white} - M_{black}) + \sum_{y=0}^{5} X_i(N_{y,white} - N_{y,black})$$

X_m: Mobility weights
M: mobility (number of available moves)
X_i: weights for all pieces without king
N_y: the number of specific types of pieces (ie. the number of white pawns)

Inducing classifier with GP

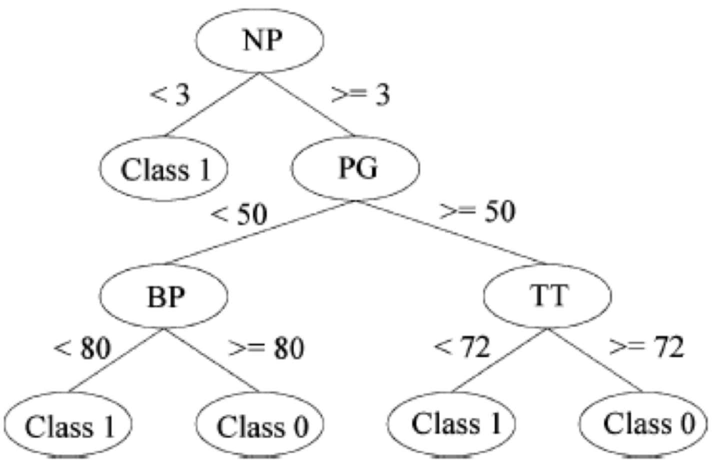
GP as search algorithm in inducing classifier

Goal: take an input and assign it to one of K discrete classes -> need to obtained a classifier

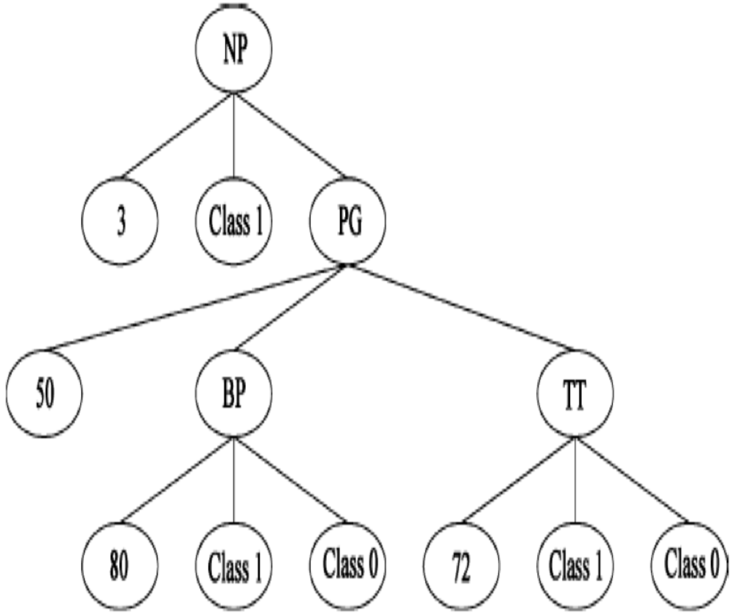
The classifier is a model encoding a set of criteria that allows a data instance to be assigned to a particular class depending on the value of certain variables.

Supervised learning: training the classifier with training data

J. R. Koza, Concept formation and decision tree induction using the genetic programming paradigm*, in Proceedings of 1st Workshop Parallel Problem Solving by Nature* 1990, pp. 124–128.



Example of decision tree

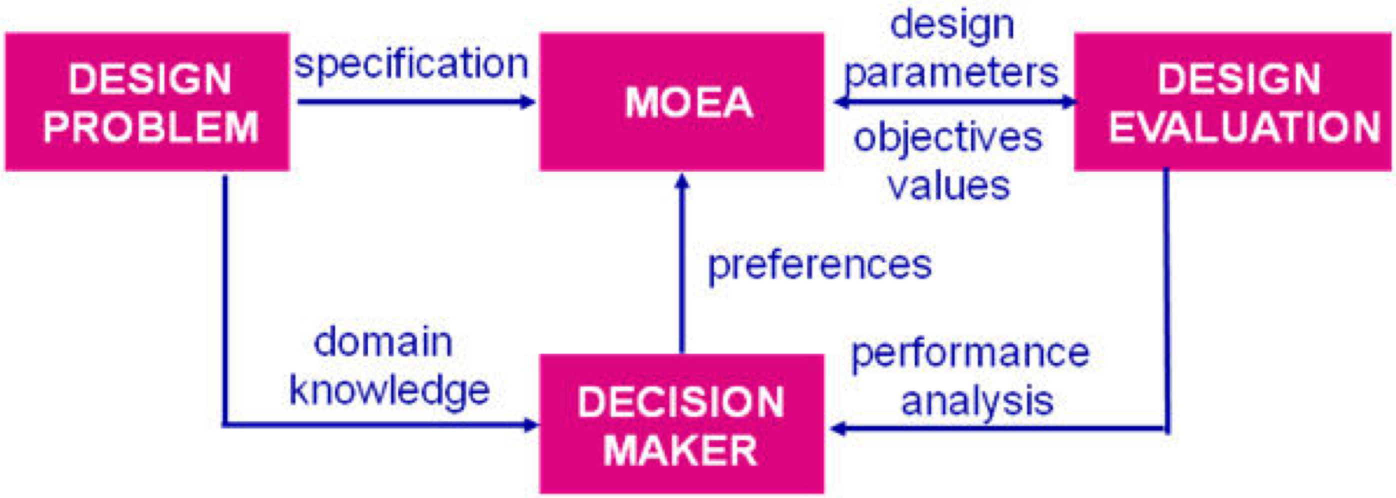


a GP individual

Applications of multiobjective EAs

- Design optimization
- Process optimization
- Image processing and image recognition
- Healthcare and bioinformatics
- …

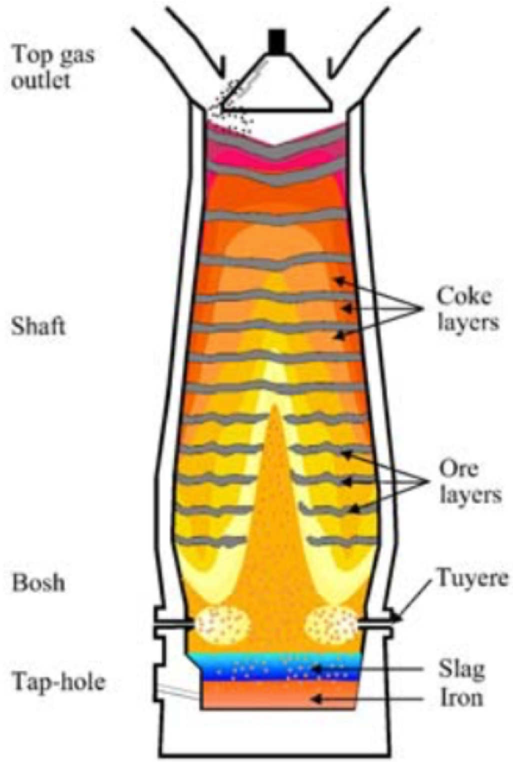
Workflow



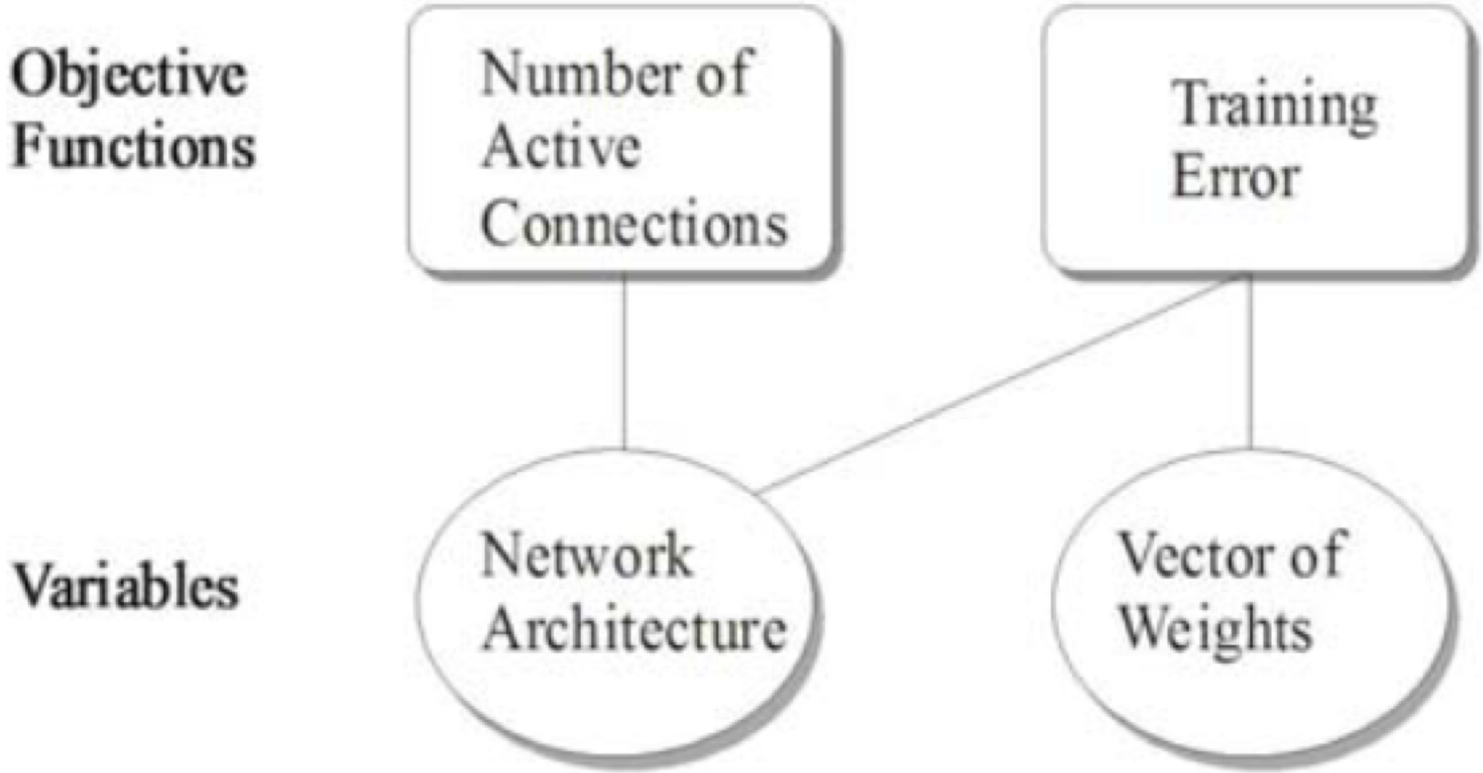
P.J. Flemming

Design of a neutral network for an industrial blast furnace

evolve a neural network that would optimally predict the carbon, sulfur and silicon contents of the hot metal produced in the blast furnace as a function of a number of process parameters.

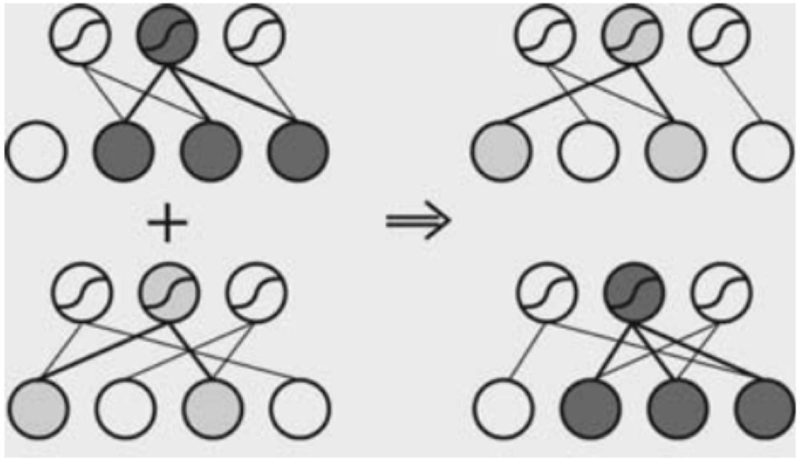


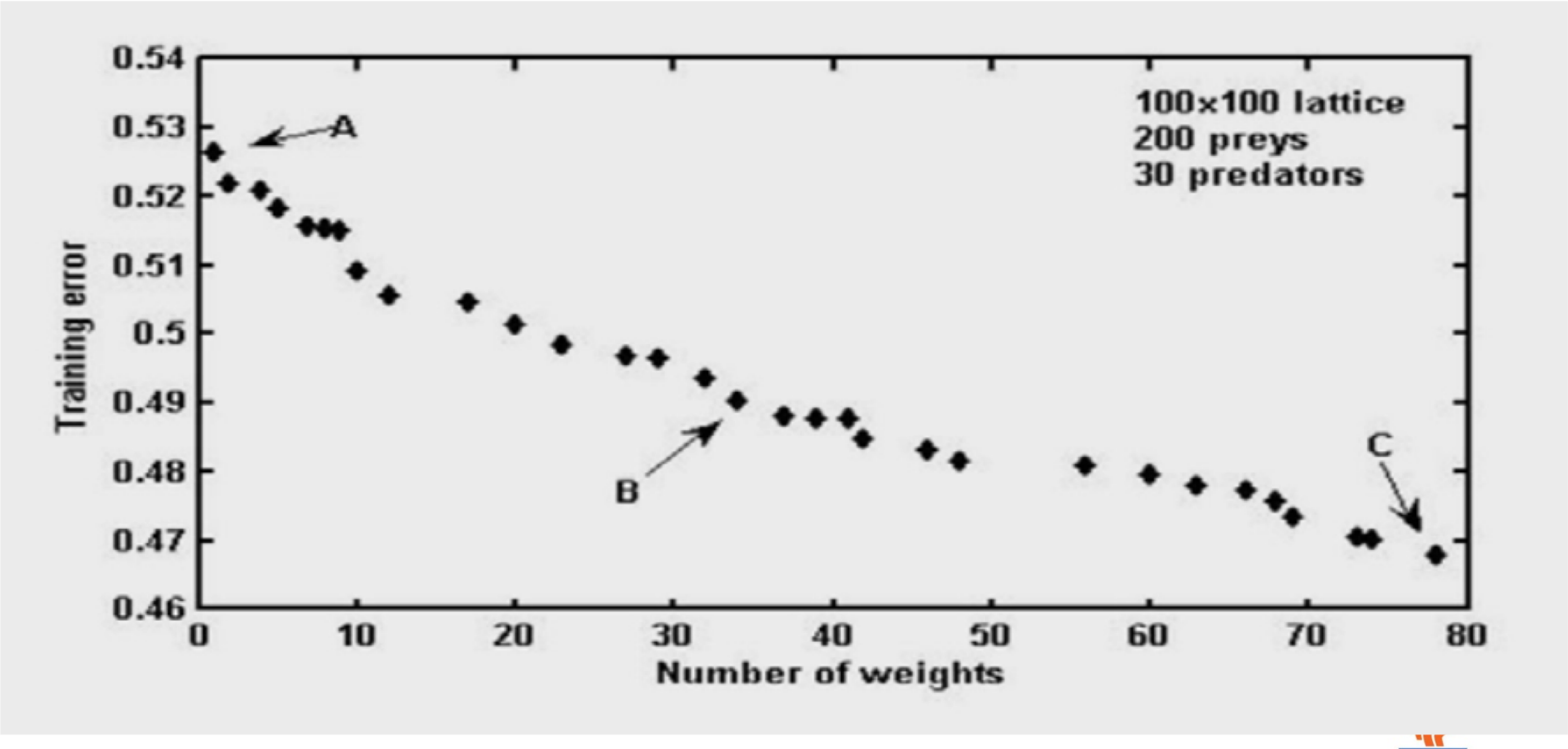
F. Pettersson, N. Chakraborti, H. Saxén,: A genetic algorithms based multiobjec-tive neural net applied to noisy blast furnace data. *Applied Soft Computing* 7, 387–397


Objective Functions
Number of Active Connections
Training Error
Variables
Network Architecture
Vector of Weights

Crossover is done on the topology

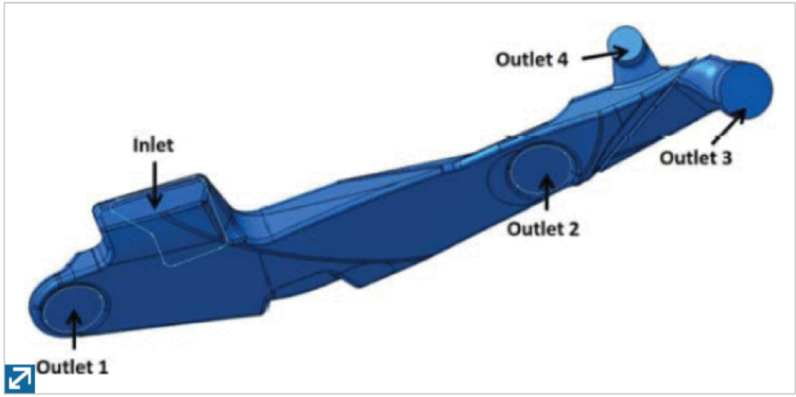
- Mutation is done on the weights





Results in a Pareto front, which the decision maker need to choose a solution to implement

Shape optimization of air intake ventilation system



f_1 : Minimize variance between flow rates at outlets 1 to 3

Minimize $var(Q_{1,3})$

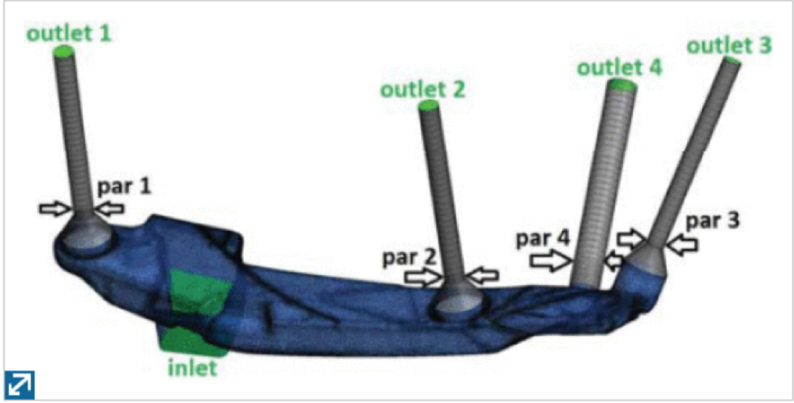
f_2 : Minimize pressure loss of the air intake

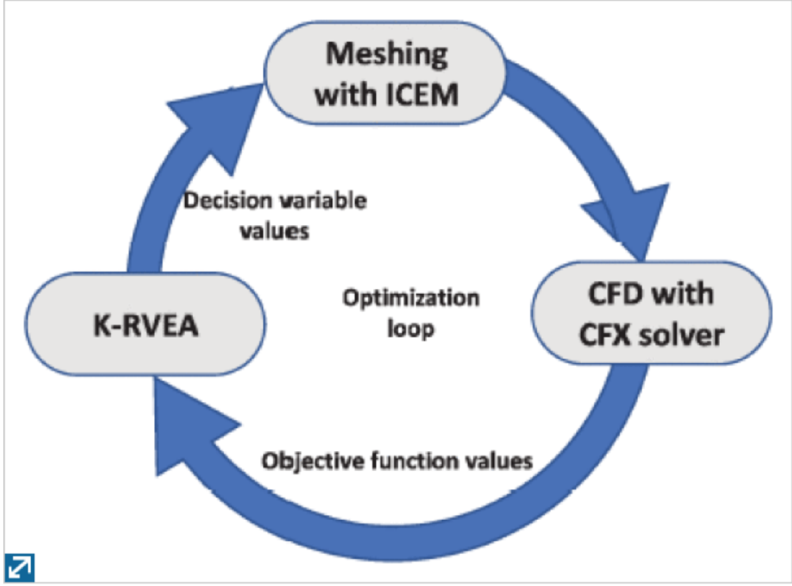
Minimize $P_{inlet} - P_{outlet}$

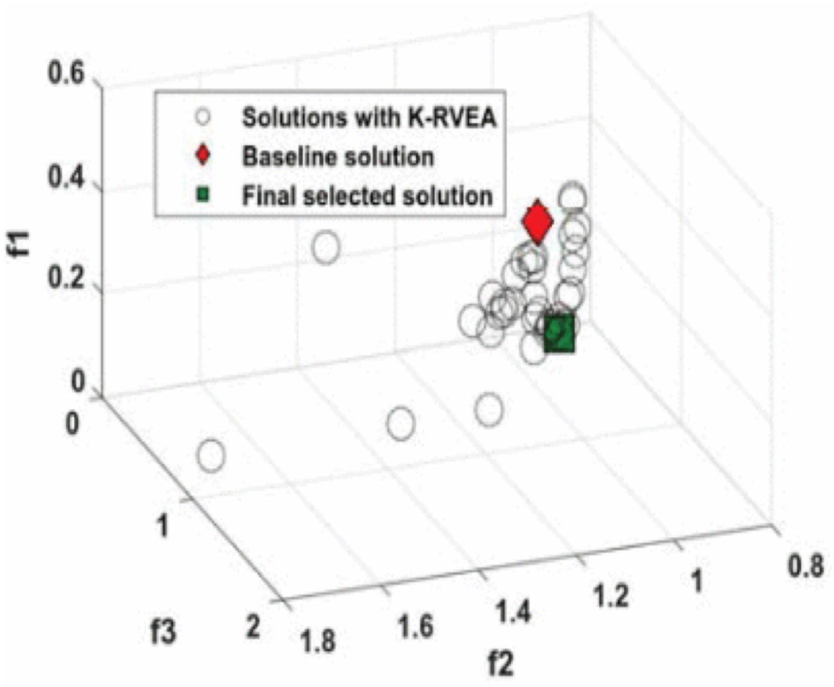
f_3 : Minimize the difference between the flow rate at outlet 4 and the average of the flow rates at outlets 1 to 3

Minimize $avg(Q_{1,3}) - Q_4$,

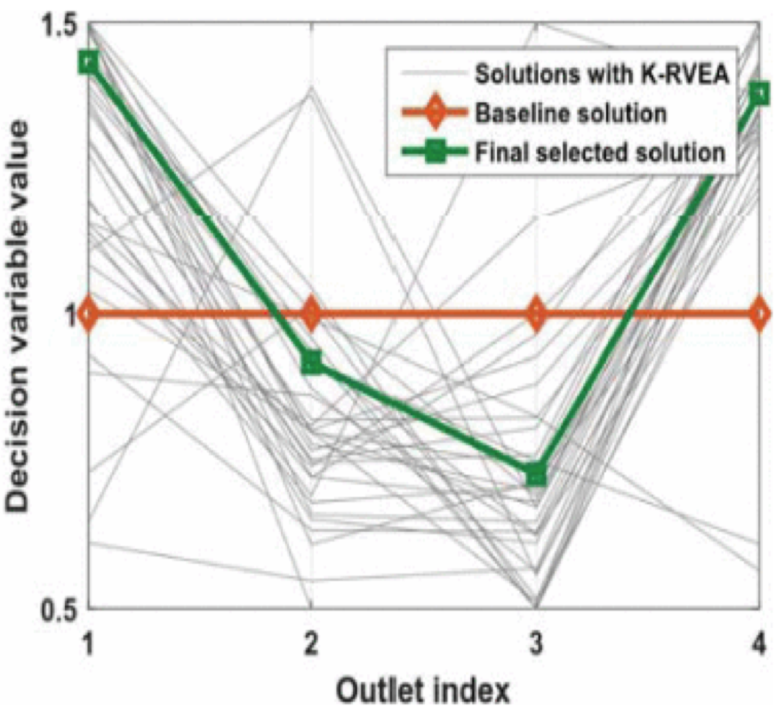
T. Chugh, K. Sindhya, K. Miettinen, Y. Jin, T. Kratky, P. Makkonen: Surrogate-assisted Evolutionary Multiobjective Shape Optimization of an Air Intake Ventilation System, *in " Proceedings of the 2017 IEEE Congress on Evolutionary Computation", IEEE*, 1541-1548, 2017


outlet 1
outlet 2
outlet 4
outlet 3
par 1
par 2
par 4
par 3
inlet

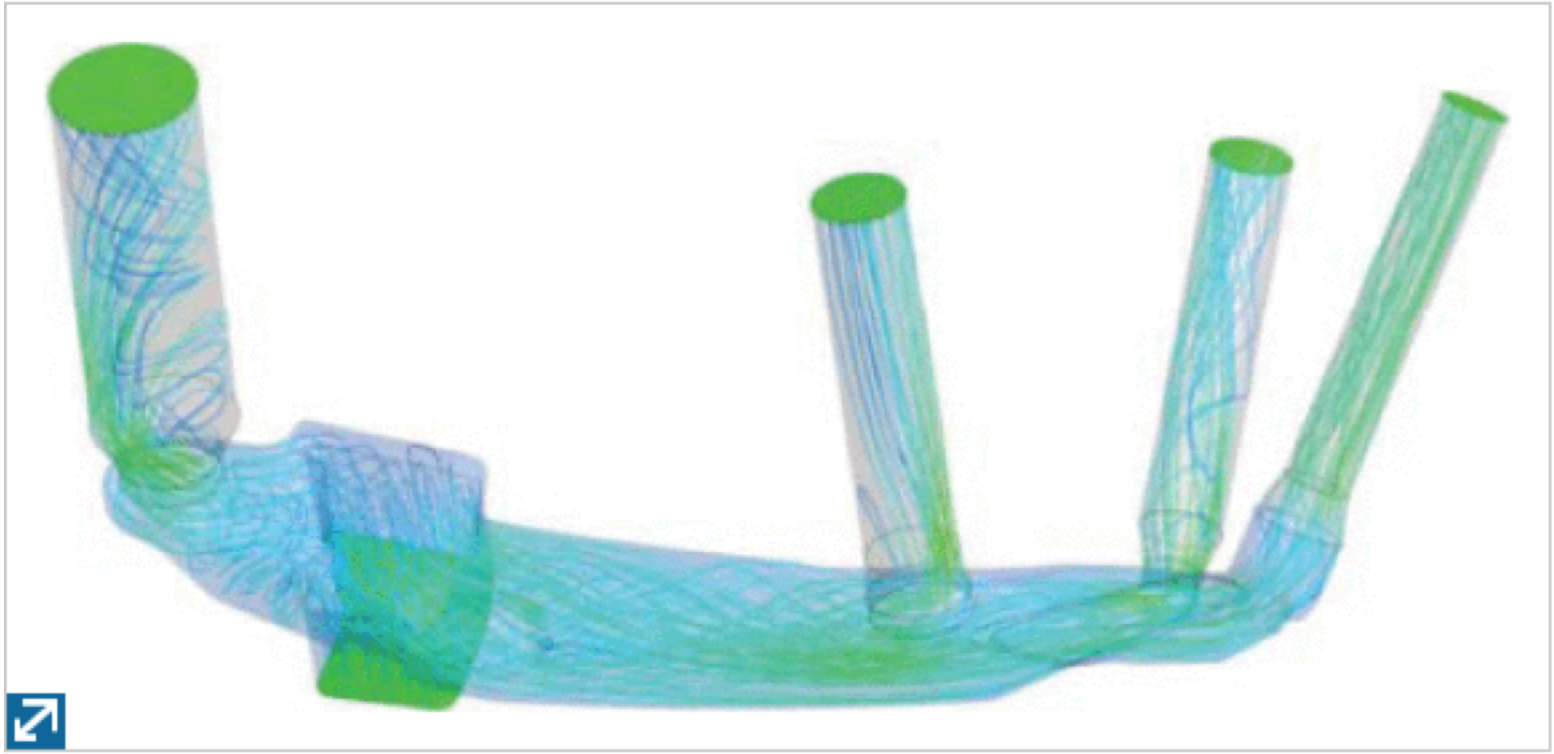

Meshing with ICEM
CFD with CFX solver
K-RVEA
Decision variable values
Optimization loop
Objective function values



Solutions with K-RVEA
Baseline solution
Final selected solution
f1
f2
f3
0.6
0.4
0.2
0
1
2
1.8
1.6
1.4
1.2
0.8

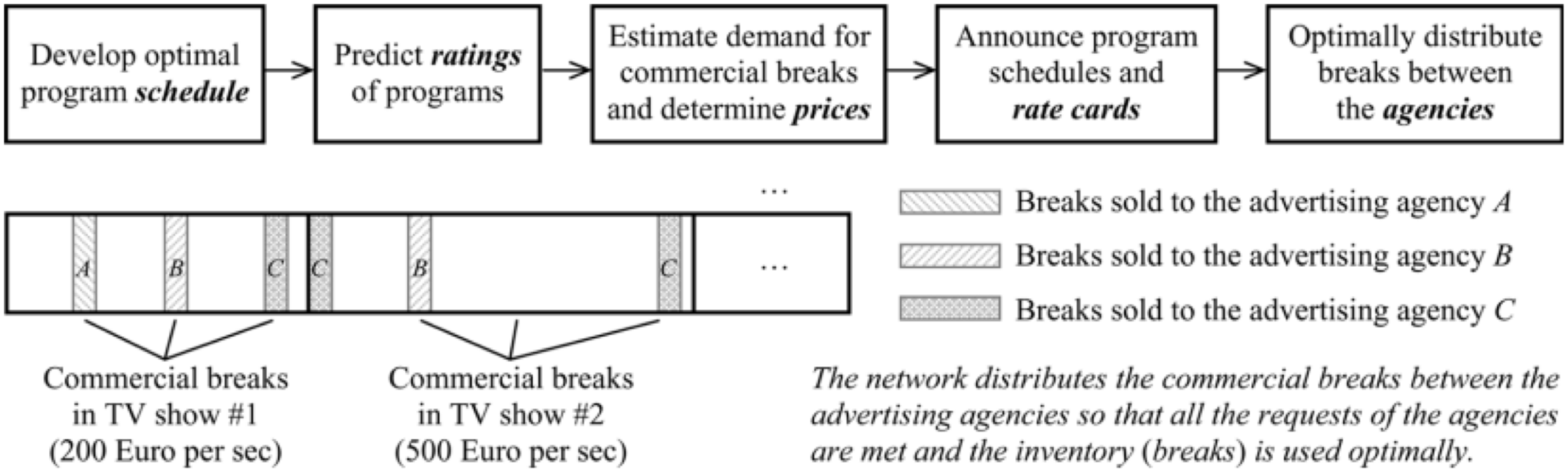


Solutions with K-RVEA
Baseline solution
Final selected solution
Decision variable value
Outlet index
1.5
1
0.5
2
3
4



Final solution selected by the decision maker

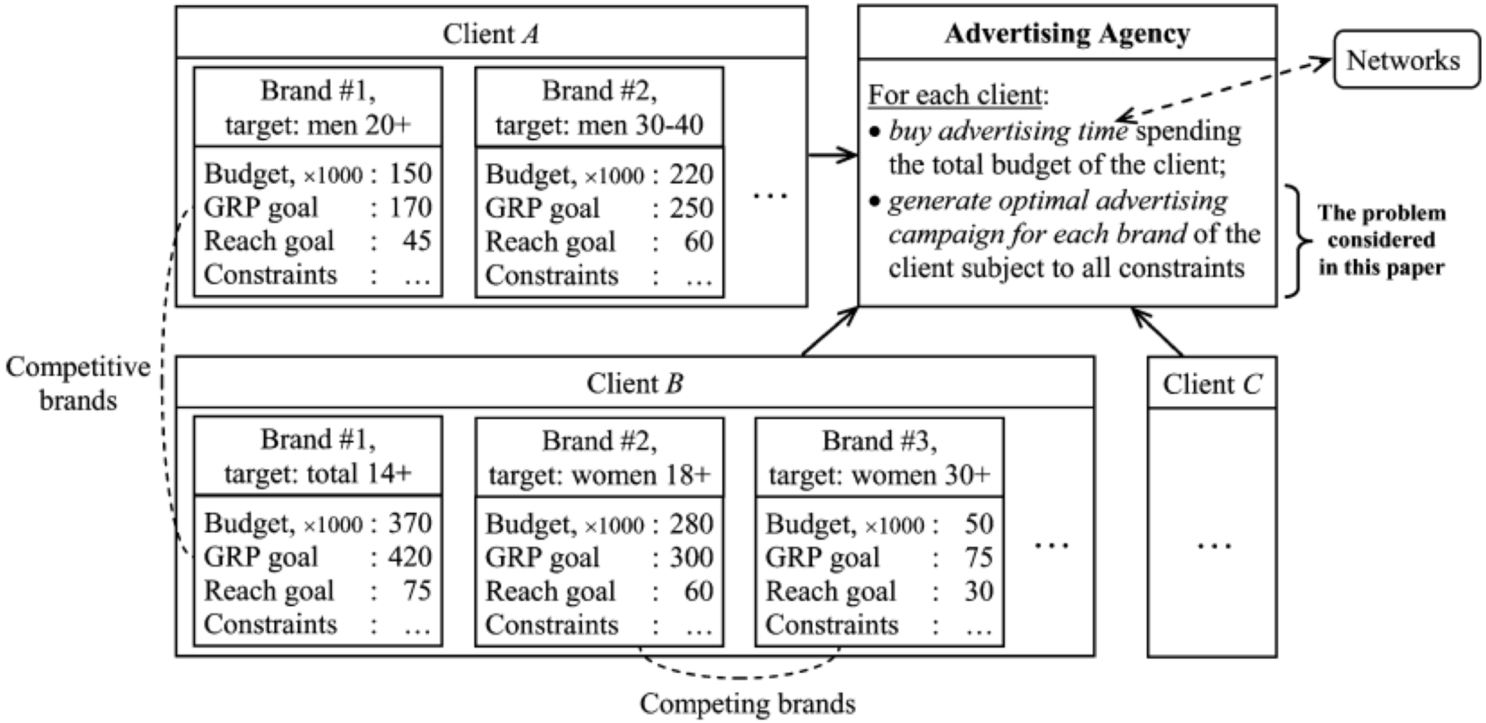
Advertising campaign generation for multiple brands



The problem from TV stations' point of view

P.J. Fleming and M.A. Pashkevich: Optimal advertising campaign generation for multiple brands using MOGA, *IEEE Trans Systems, Man and Cybernetics*, 37, pp. 1190-1201, 2007.

For major clients, the agency buys the advertising time from the networks spending the total budget of brands that the client company is advertising, and performs the actual distribution of the airing time between the brands on a later stage. This NP-hard combinatorial optimization problem is one of the key issues the agency has to deal with.



The problem from advertising agencies' point of view

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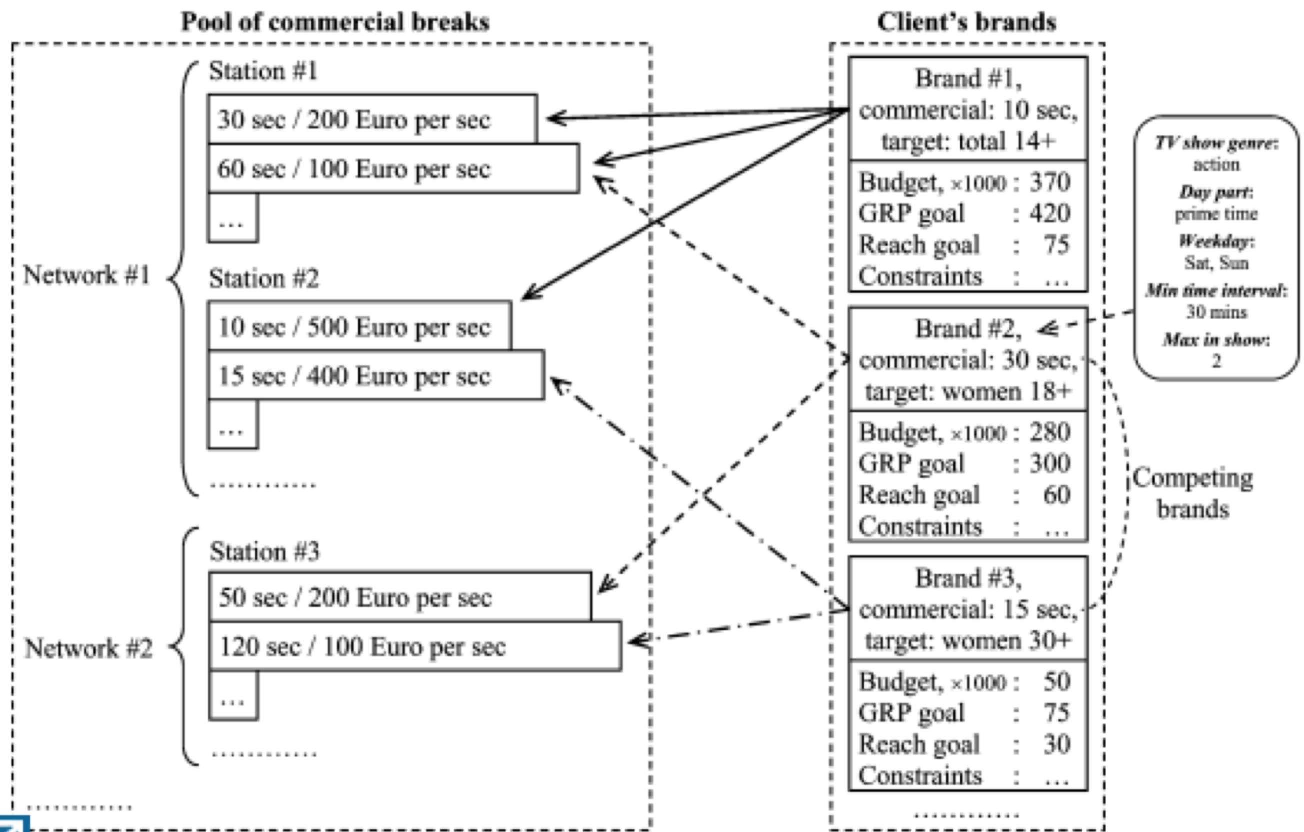
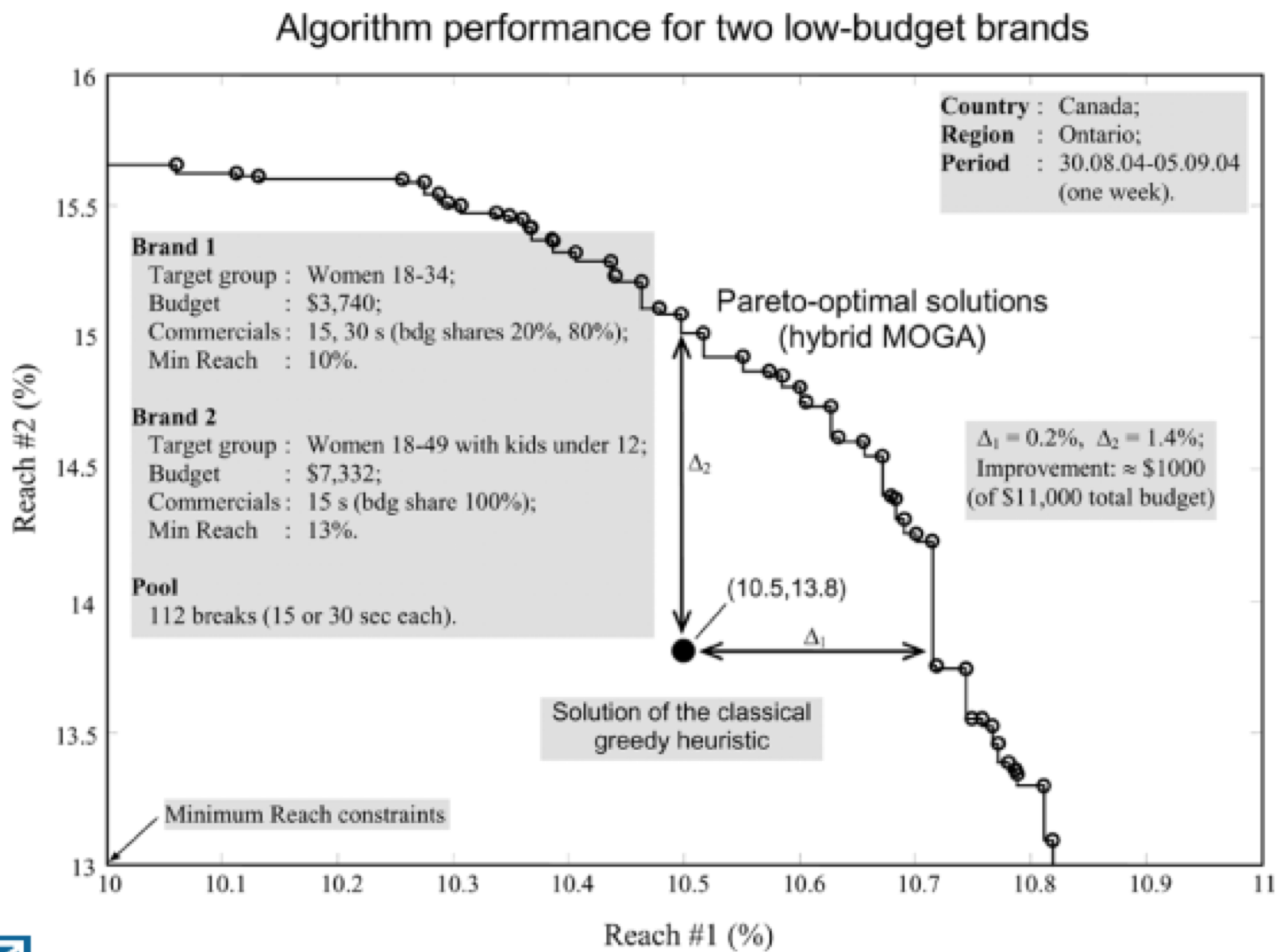
The advertising time purchased by the agency for the client company from the TV networks (pool of commercial breaks) must be optimally distributed among the brands that the company is advertising (client's brands). While generating the mediaplan, the agency accounts for a number of constraints for each brand that include: budget limit, minimum values of Reach and GRP, genre and location of shows where the commercials should be placed. Besides, length of each commercial break is limited, and the competing brands can not be aired in one break.



Objectives: maximize the reach of each brand



Algorithm performance for two low-budget brands
Country : Canada;
Region : Ontario;
Period : 30.08.04-05.09.04 (one week).
Brand 1
Target group : Women 18-34;
Budget : $3,740;
Commercials : 15, 30 s (bdg shares 20%, 80%);
Min Reach : 10%.
Brand 2
Target group : Women 18-49 with kids under 12;
Budget : $7,332;
Commercials : 15 s (bdg share 100%);
Min Reach : 13%.
Pool
112 breaks (15 or 30 sec each).
Pareto-optimal solutions (hybrid MOGA)
Δ1 = 0.2%, Δ2 = 1.4%;
Improvement: ≈ $1000
(of $11,000 total budget)
(10.5,13.8)
Δ2
Δ1
Solution of the classical greedy heuristic
Minimum Reach constraints
Reach #2 (%)
Reach #1 (%)
16
15.5
15
14.5
14
13.5
13
10
10.1
10.2
10.3
10.4
10.5
10.6
10.7
10.8
10.9
11

Other interesting applications

Hybrid electric vehicle control

R. Cheng, T. Rodemann, M. Fischer, M. Olhofer and Y. Jin: Evolutionary Many-Objective Optimization of Hybrid Electric Vehicle Control: From General Optimization to Preference Articulation, in *IEEE Transactions on Emerging Topics in Computational Intelligence*, 1(2), pp. 97-111, 2017.

High-speed train nose

M. SUZUKI, K. NAKADE: Multi-Objective Design Optimization of High-Speed Train Nose, *Journal of Mechanical Systems for Transportation and Logistics*, 6(1), pp. 54-64, 2013

Knowledge-driven evolutionary optimization

K.Deb, A. Srinivasan: Innovization: Discovery of Innovative Design Principles Through Multiobjective Evolutionary Optimization, *in proceedings of Multiobjective Problem Solving from Nature*, pp. 243-262, 2008.

Useful links

Collection about differential evolution:
http://www1.icsi.berkeley.edu/~storn/code.html

Collection about particle swarm optimization:
http://www.swarmintelligence.org

Collection of literature of multiobjective evolutionary algorithms:
http://neo.lcc.uma.es/emoo/EMOObib.html

MOEA/D homepage
http://dces.essex.ac.uk/staff/zhang/webofmoead.htm

JYVÄSKYLÄN YLIOPISTO
UNIVERSITY OF JYVÄSKYLÄ