Multi-Objective Optimization of a Tube Bundle Heat Exchanger

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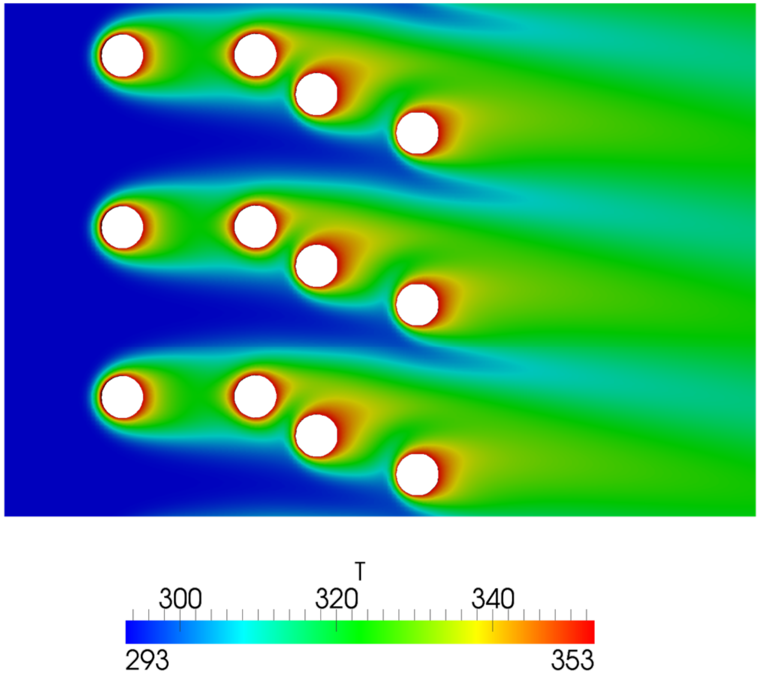
- Geometry optimization
- Heat exchanger problem
- Workflow
- Software
- Case setup
- Results
- Work in progress and in the future

Geometry Optimization

Heat exchanger

$\max(\Delta T)$ and $\min(\Delta p)$

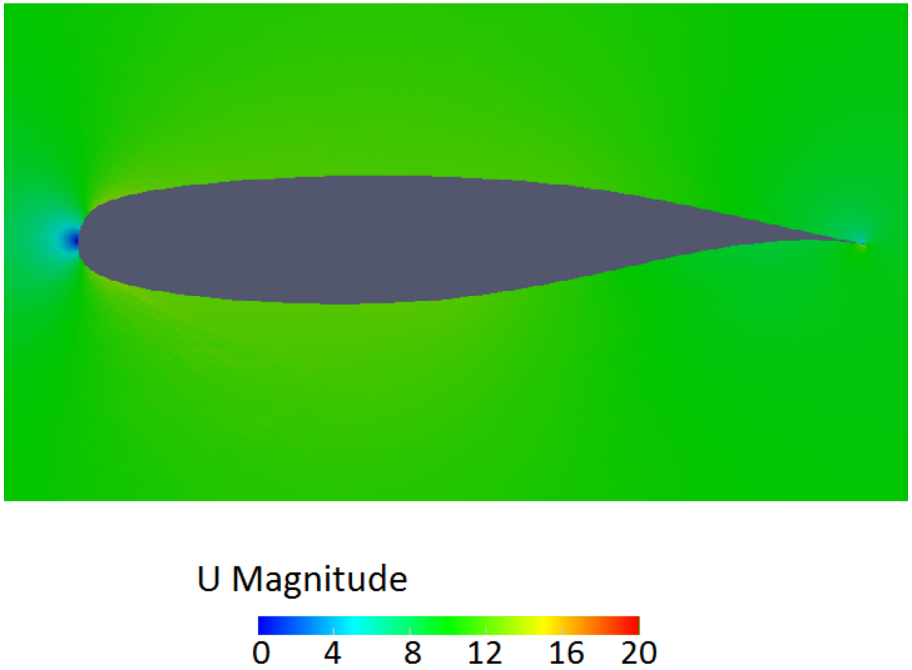
Tube position optimization



Airfoil

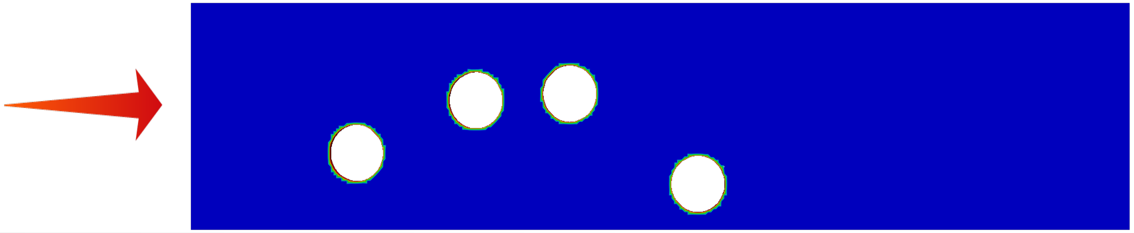
$\max(C_L)$ and $\min(C_D)$

Shape optimization

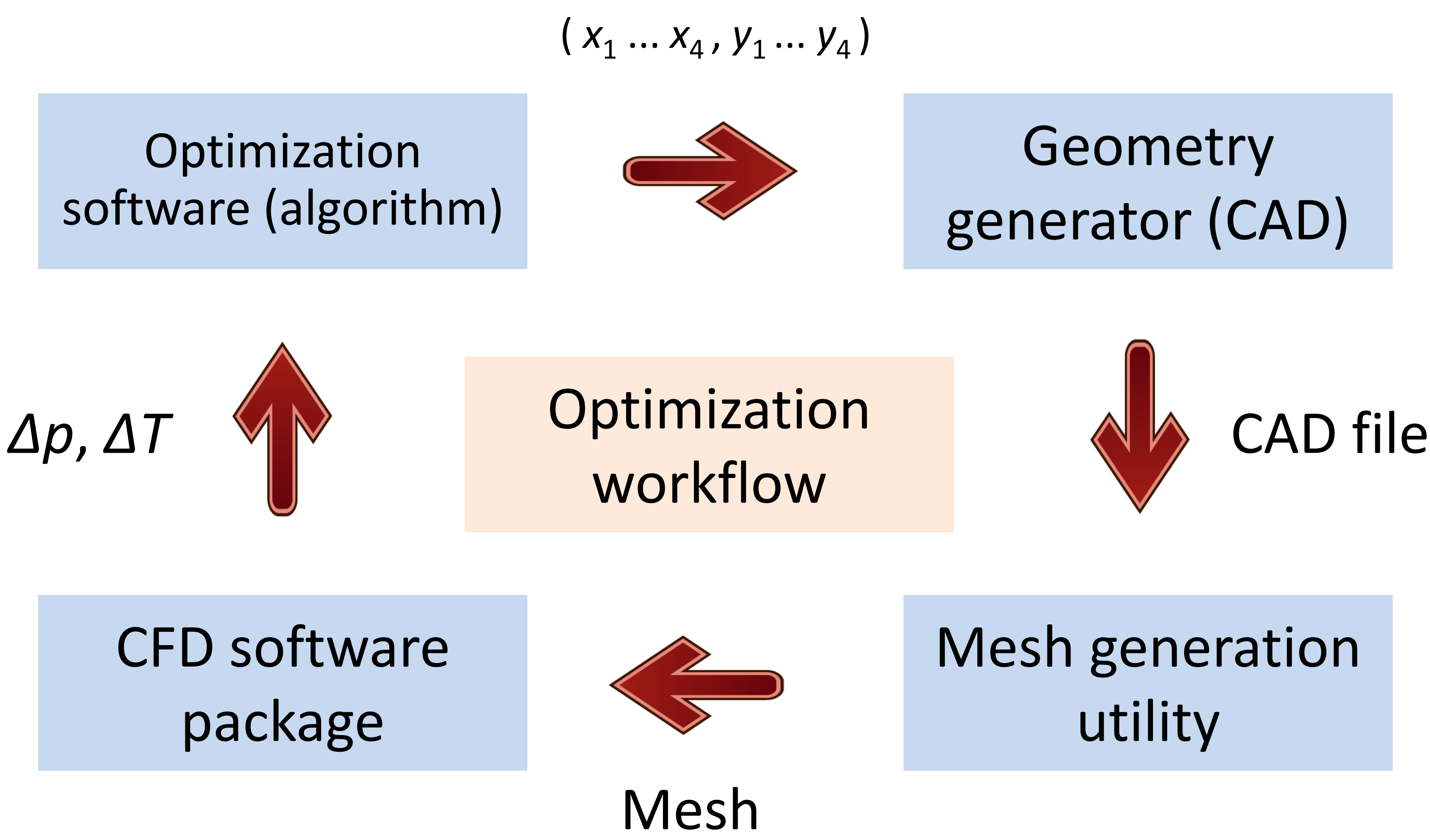


Heat Exchanger Problem

- Objective:
  - Find optimal tube positions for maximum temperature increase and minimum pressure drop
- Parameters:
  - Tube positions – coordinates ($x_1 \ldots x_4$, $y_1 \ldots y_4$)
- Objective Functions:
  - Pressure drop, Δp
  - Temperature increase, ΔT
- Constraints:
  - Tubes cannot be in contact (two different approaches):
    - restricting *x* position (*x*-corridor)
    - nonlinear distance constraints
- 2D case

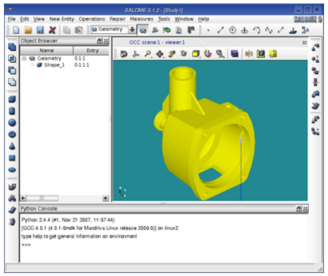


Workflow


($x_1 \dots x_4$, $y_1 \dots y_4$)
Optimization software (algorithm)
Geometry generator (CAD)
Δp, ΔT
Optimization workflow
CAD file
CFD software package
Mesh generation utility
Mesh

Software

- **Dakota** (Sandia National Laboratories)
  - A Multilevel Parallel Object-Oriented Framework for:
    - Design Optimization
    - Parameter Estimation
    - Uncertainty Quantification
    - Sensitivity Analysis
  - Here: Evolutionary Algorithm (derivative-free global algorithm)
- **Salome** (EDF, CEA, OpenCascade)
  - CAD and Post-Processing
  - Graphical user and terminal user interface
  - Here: TUI with python script for cylinder geometry generation



- **OpenFOAM**
  - Meshing (blockMesh and snappyHexMesh)
  - Solver (buoyantBoussinesqSimpleFoam)
  - Post-processing (swak4Foam): Average pressure drop and temperature increase from inlet to outlet

Software

Dakota
(EA algorithm)

Optimization
software (algorithm)

$(x_1 \dots x_4 , y_1 \dots y_4)$

Salome
(python script)

Geometry
generator (CAD)

STL file

Optimization
workflow

Δp, ΔT

Mesh generation
utility

OpenFOAM
(meshing)

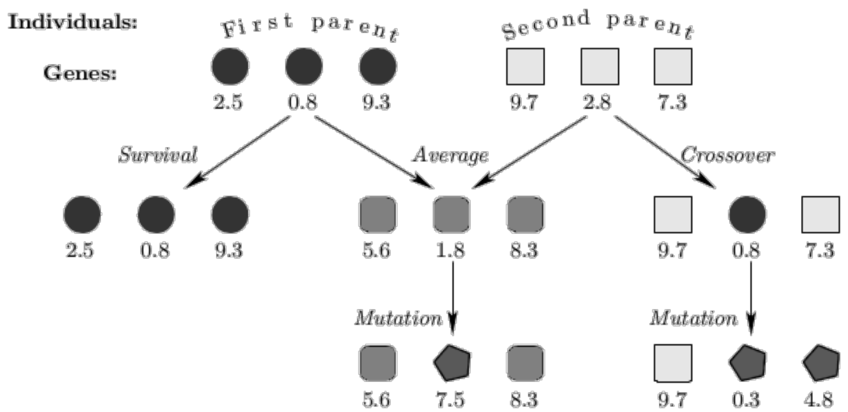
Mesh

CFD software
package

OpenFOAM
(solver)

Case setup - *Dakota*

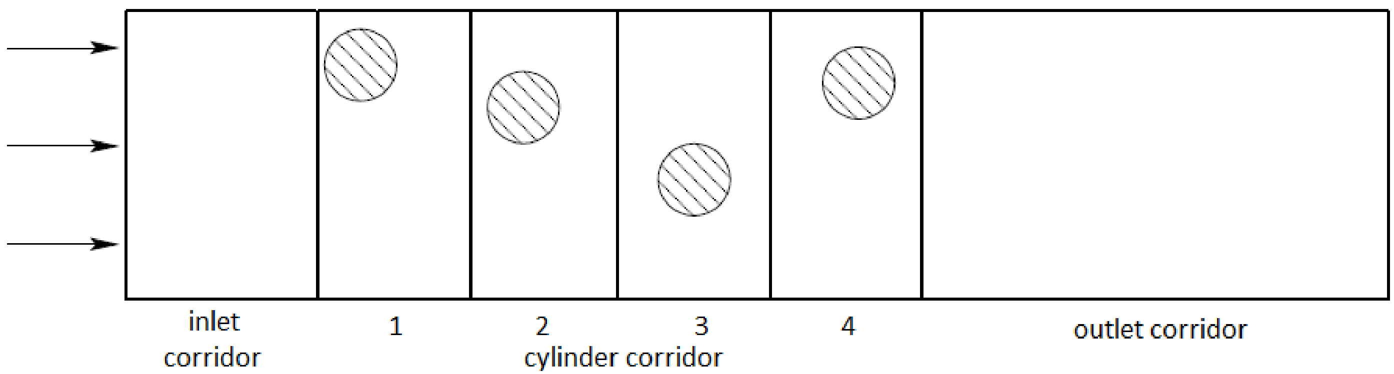
- Method:
  - Multi-objective genetic algorithm MOGA (JEGA library)
    - Population sizes: 40, 60, 80
    - Number of generations: 5, 10 ,15, 20
    - Crossover type – *shuffle random*
      - number of parents = population size
      - number of children = 75% of population
    - Mutation type – *offset normal*
      - mutation rate = 100%
      - mutation scale = 10%
    - Replacement type – *elitist*



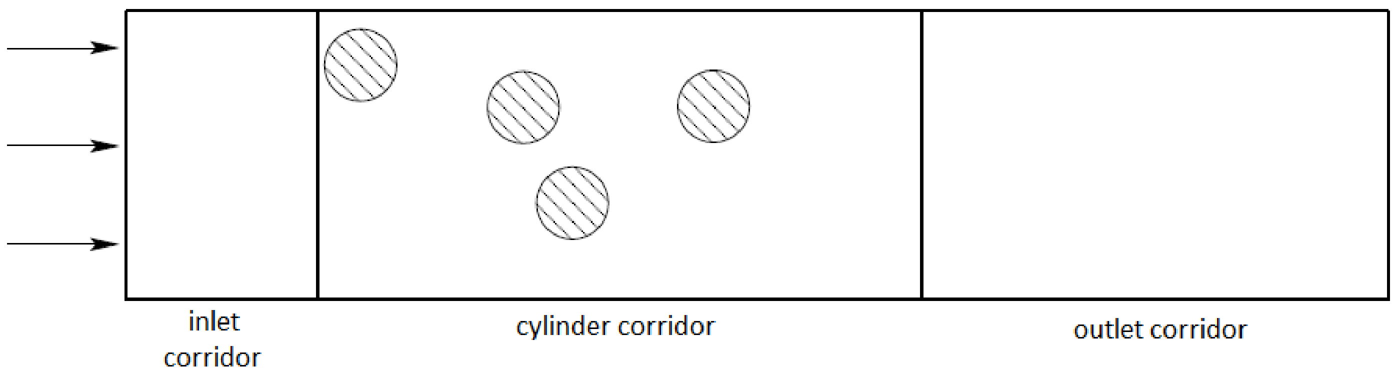
- Variables:
  - 8 variables (x_1 ... x_4 , y_1 ... y_4)
  - Constraints (two approaches):
    - 6 x-corridors: inlet corridor, 4 tube corridors, outlet corridot
    - 3 x-corridors: inlet corridor, tube corridor, outlet corridor – minimal tube distance as a constraint
- Response functions:
  - 6 x-corridors – 2 response functions: Δp, ΔT
  - 3 x-corridors – 8 response functions: Δp, ΔT, 6 distance values between cylinders

Case setup - *Dakota*

- 6 x-corridors

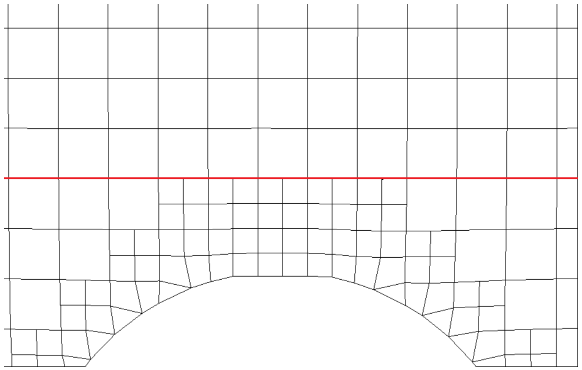


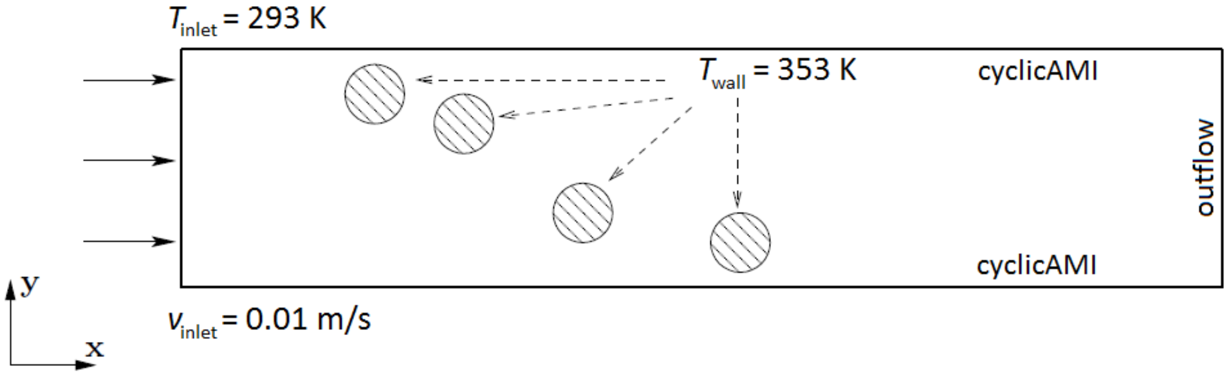
- 3 x-corridors



Case setup - *OpenFOAM*

- Fluid - Air
- Boundary conditions:
  - Inlet – *velocity inlet*
    - U = (0.01 0 0) m/s
    - T = 293 K
    - Re = 14 (laminar flow, steady state)
  - Top and bottom – *cyclicAMI*
  - Cylinders - *wall*
    - constant temperature, T = 353 K
  - Outflow
    - p = 0 Pa (gauge pressure)
- Post-processing (*swak4Foam*) – Δp_{avg} and ΔT_{avg}

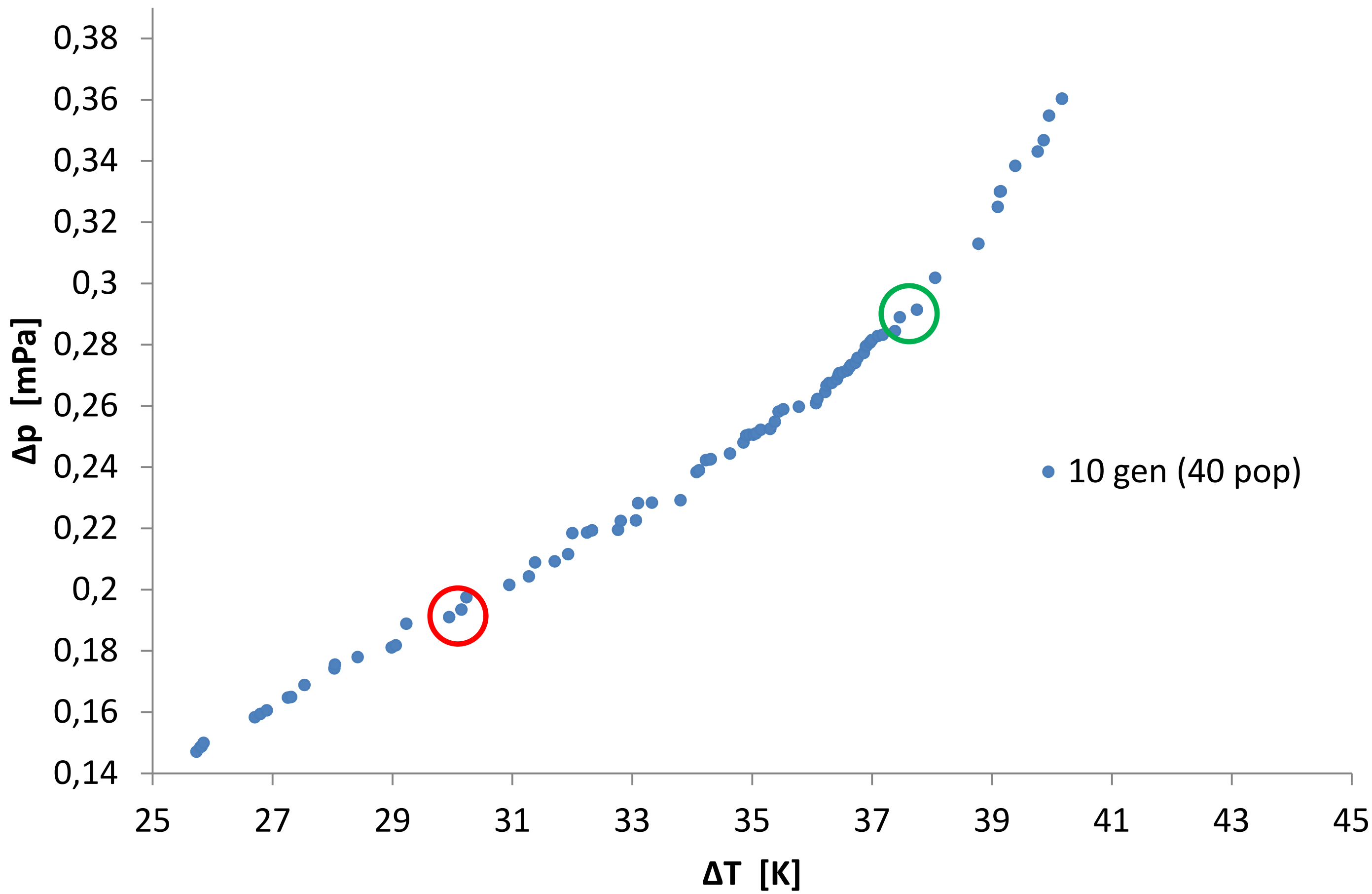




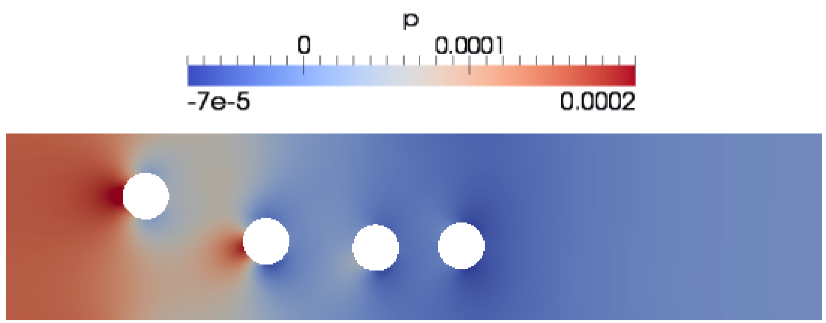
Results

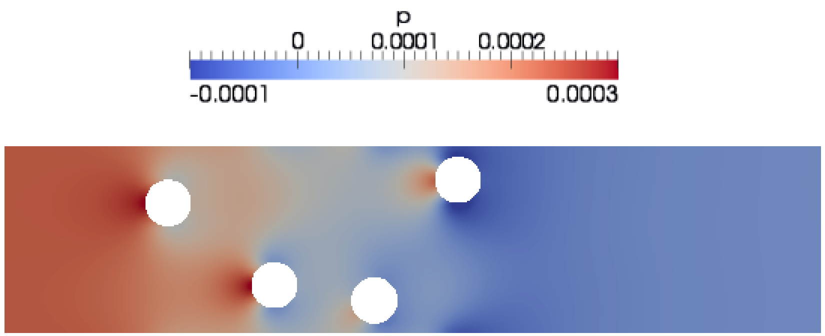
Results

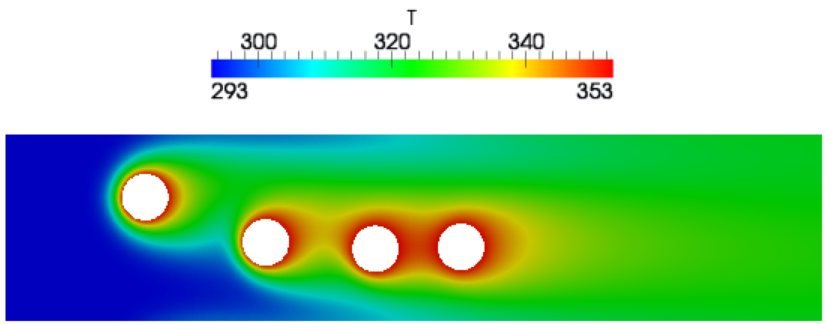
- The result of the bi-objective optimization is the Pareto-front – the line of optimal solutions.

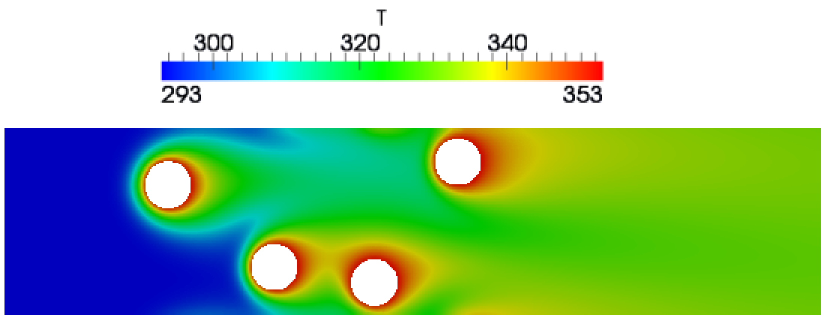


Results





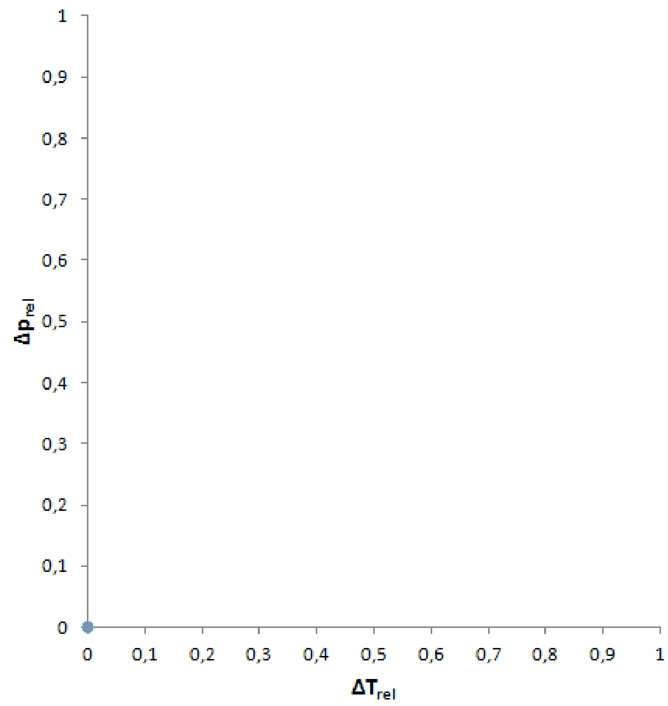




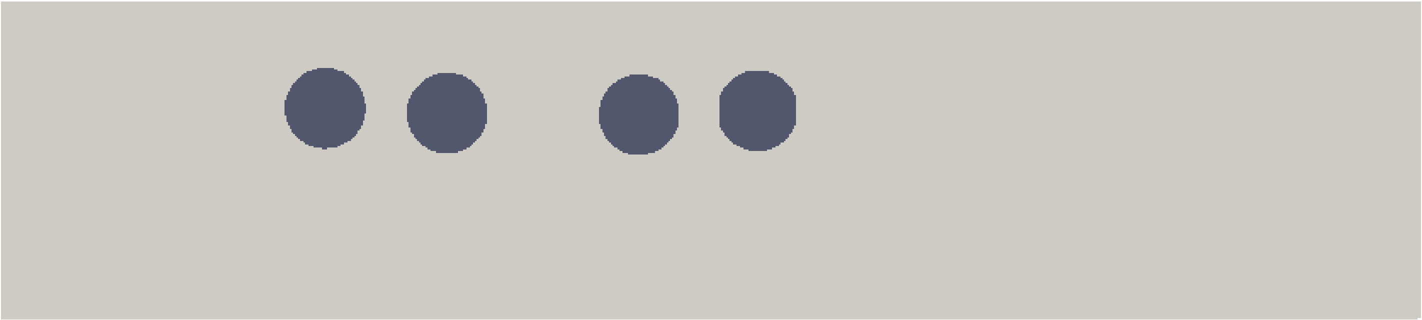
$\Delta p = 0.19$ mPa
$\Delta T = 29.95$ K

$\Delta p = 0.29$ mPa
$\Delta T = 37.75$ K

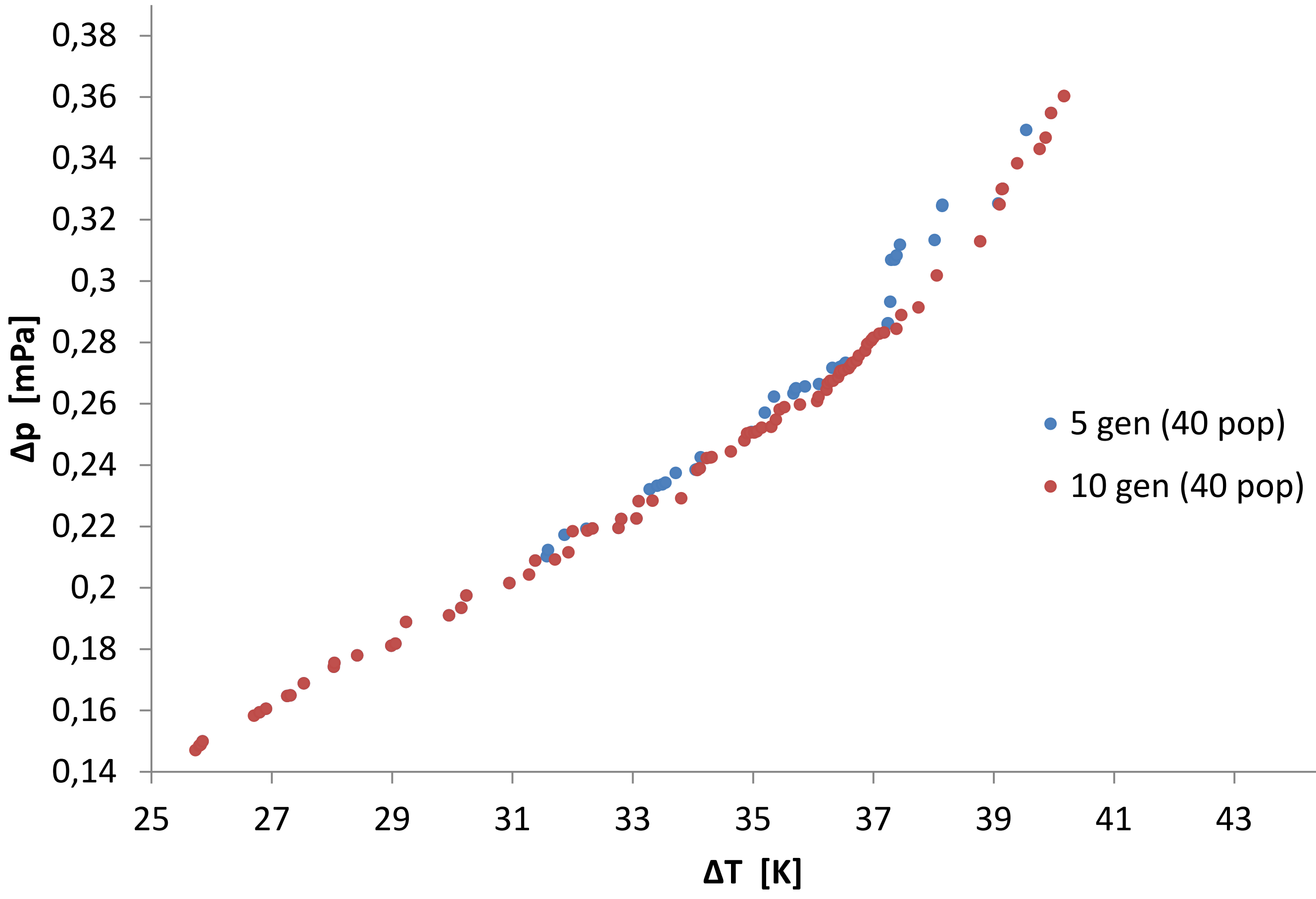
Results



1
0,9
0,8
0,7
0,6
0,5
0,4
0,3
0,2
0,1
0
Δp_{rel}
0 0,1 0,2 0,3 0,4 0,5 0,6 0,7 0,8 0,9 1
ΔT_{rel}

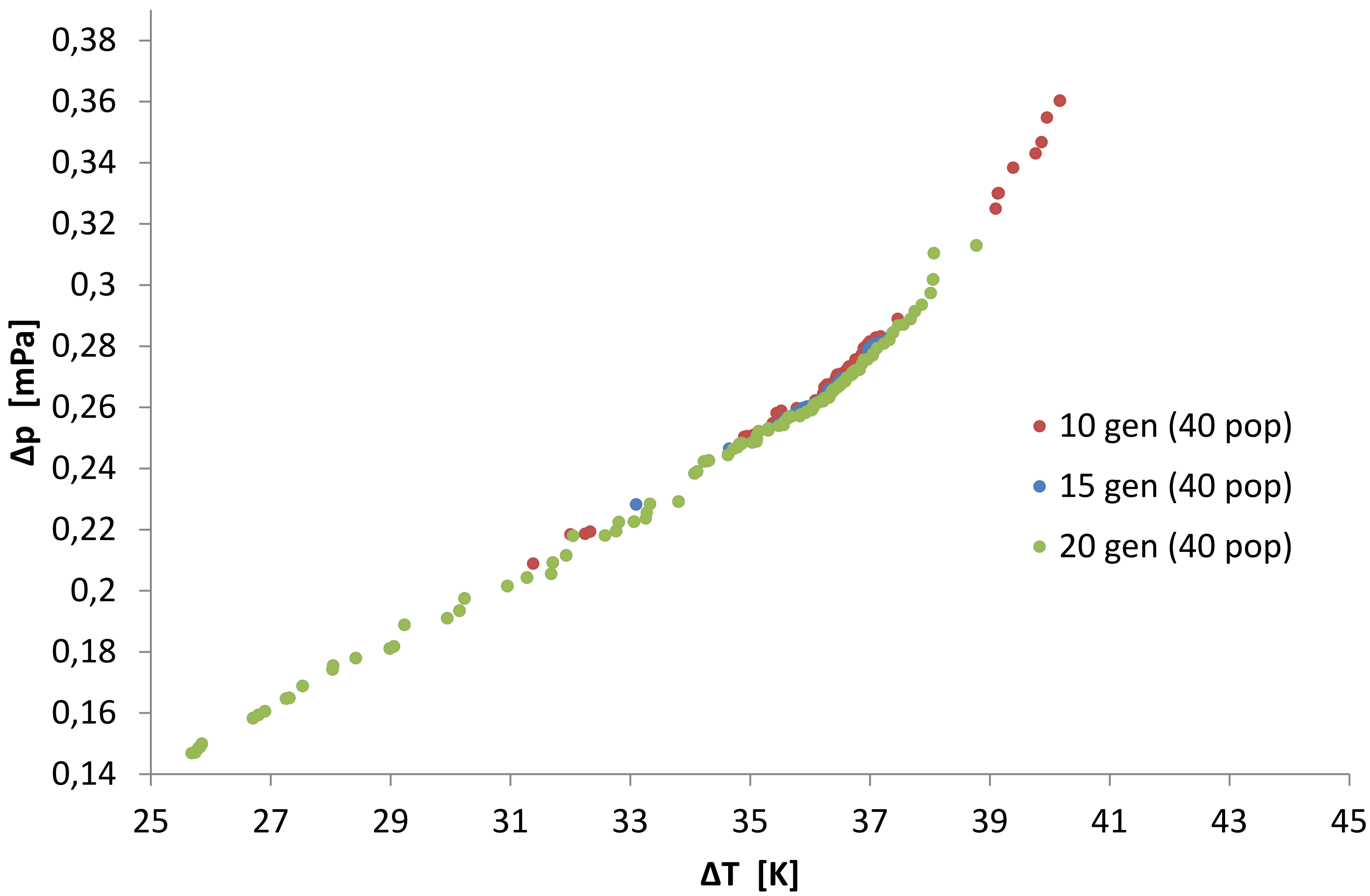


Results



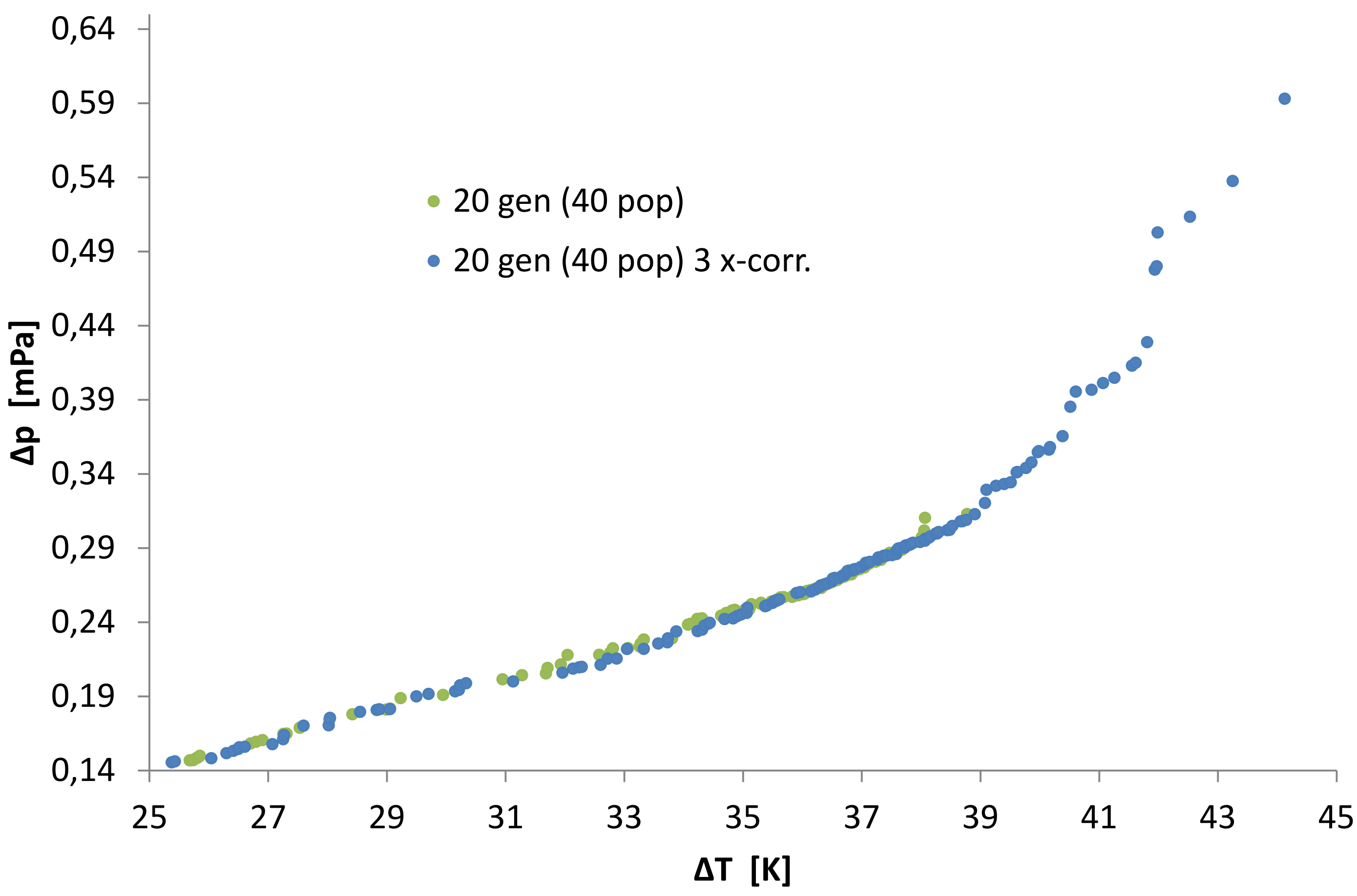
0,38
0,36
0,34
0,32
0,3
0,28
0,26
0,24
0,22
0,2
0,18
0,16
0,14
Δp [mPa]
25
27
29
31
33
35
37
39
41
43
45
ΔT [K]
5 gen (40 pop)
10 gen (40 pop)

Results



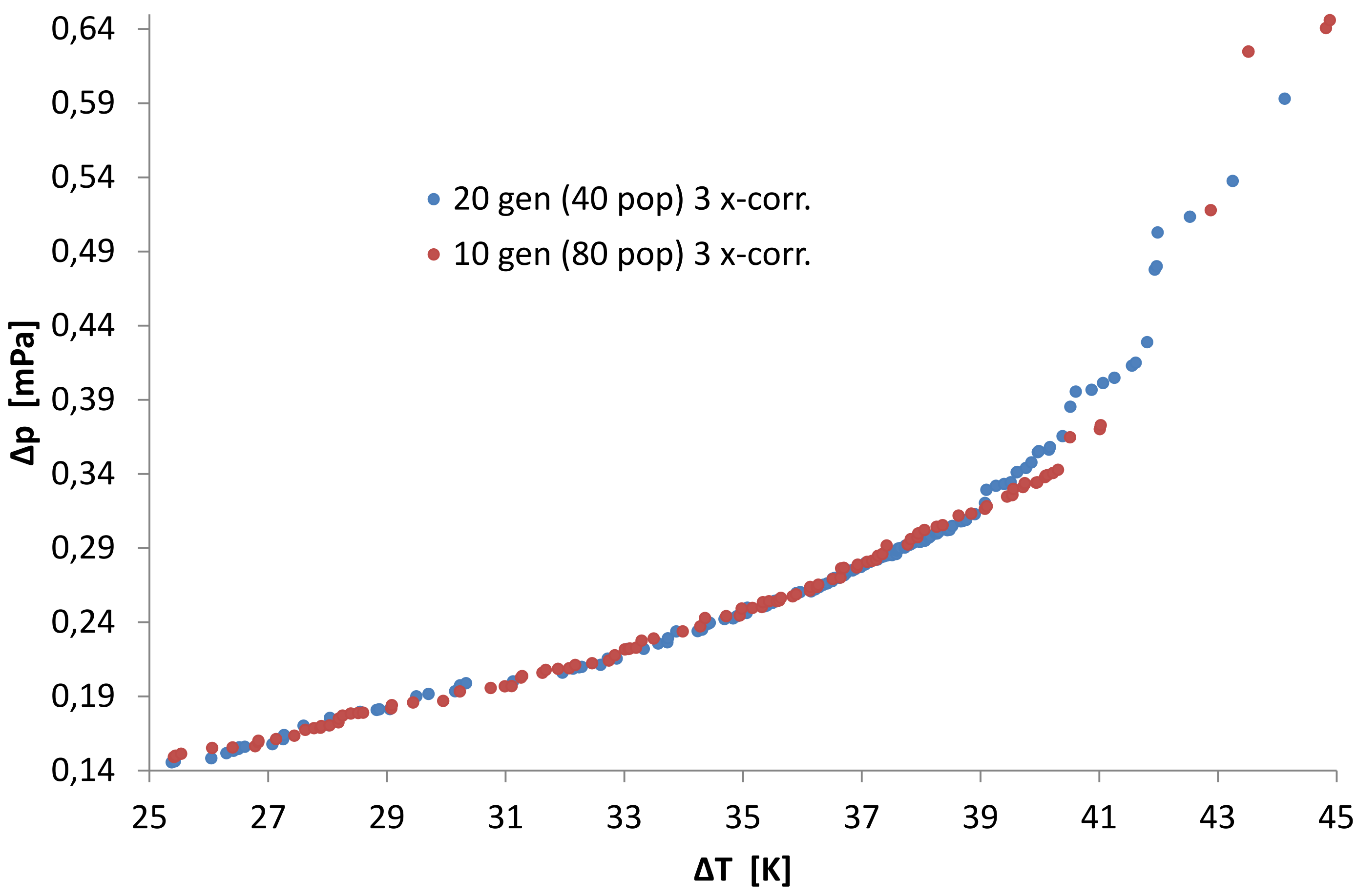
0,38
0,36
0,34
0,32
0,3
0,28
0,26
0,24
0,22
0,2
0,18
0,16
0,14
Δp [mPa]
25
27
29
31
33
35
37
39
41
43
45
ΔT [K]
10 gen (40 pop)
15 gen (40 pop)
20 gen (40 pop)

Results



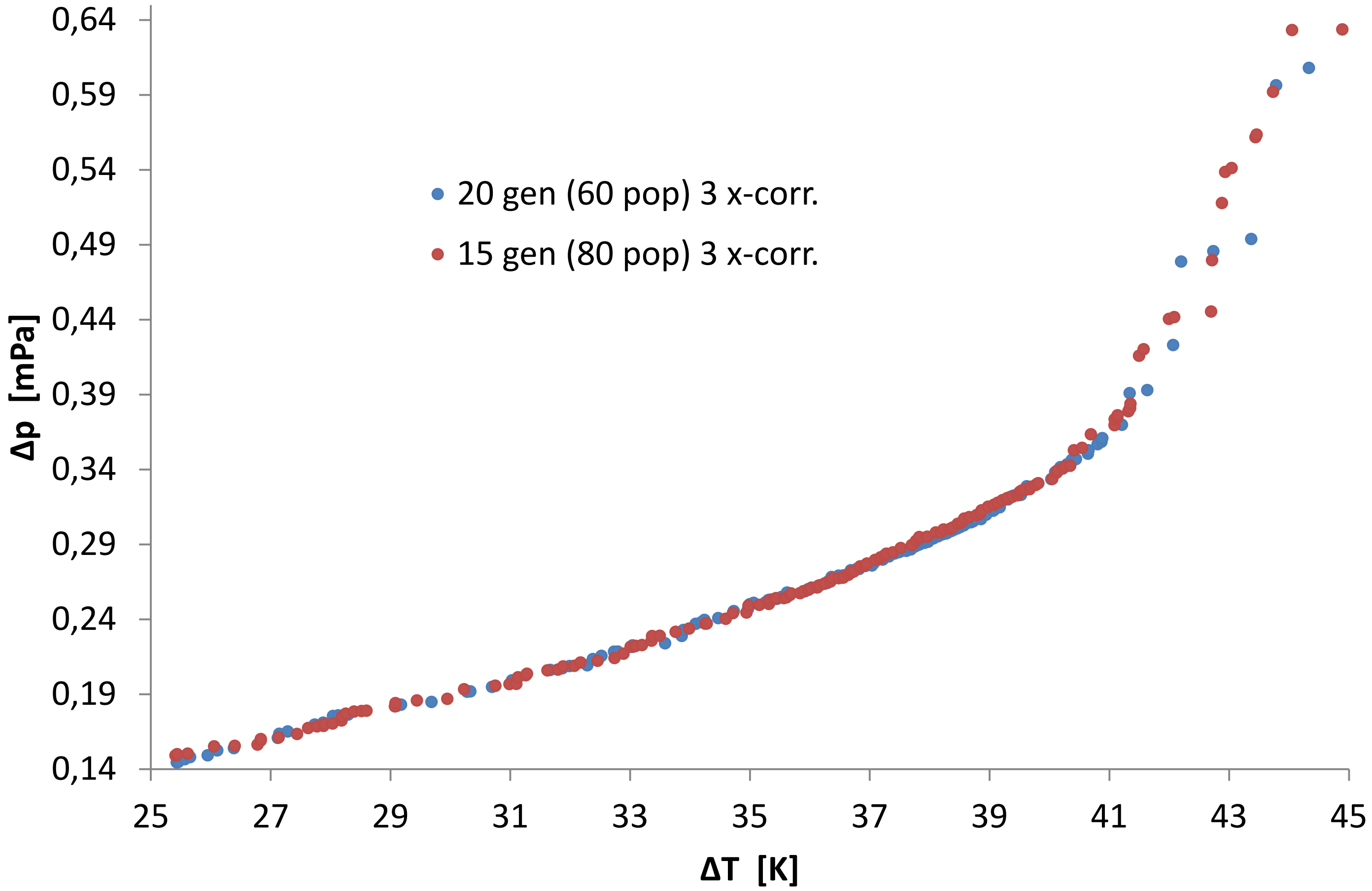
0,64
0,59
0,54
0,49
0,44
0,39
0,34
0,29
0,24
0,19
0,14
Δp [mPa]
25
27
29
31
33
35
37
39
41
43
45
ΔT [K]
20 gen (40 pop)
20 gen (40 pop) 3 x-corr.

Results



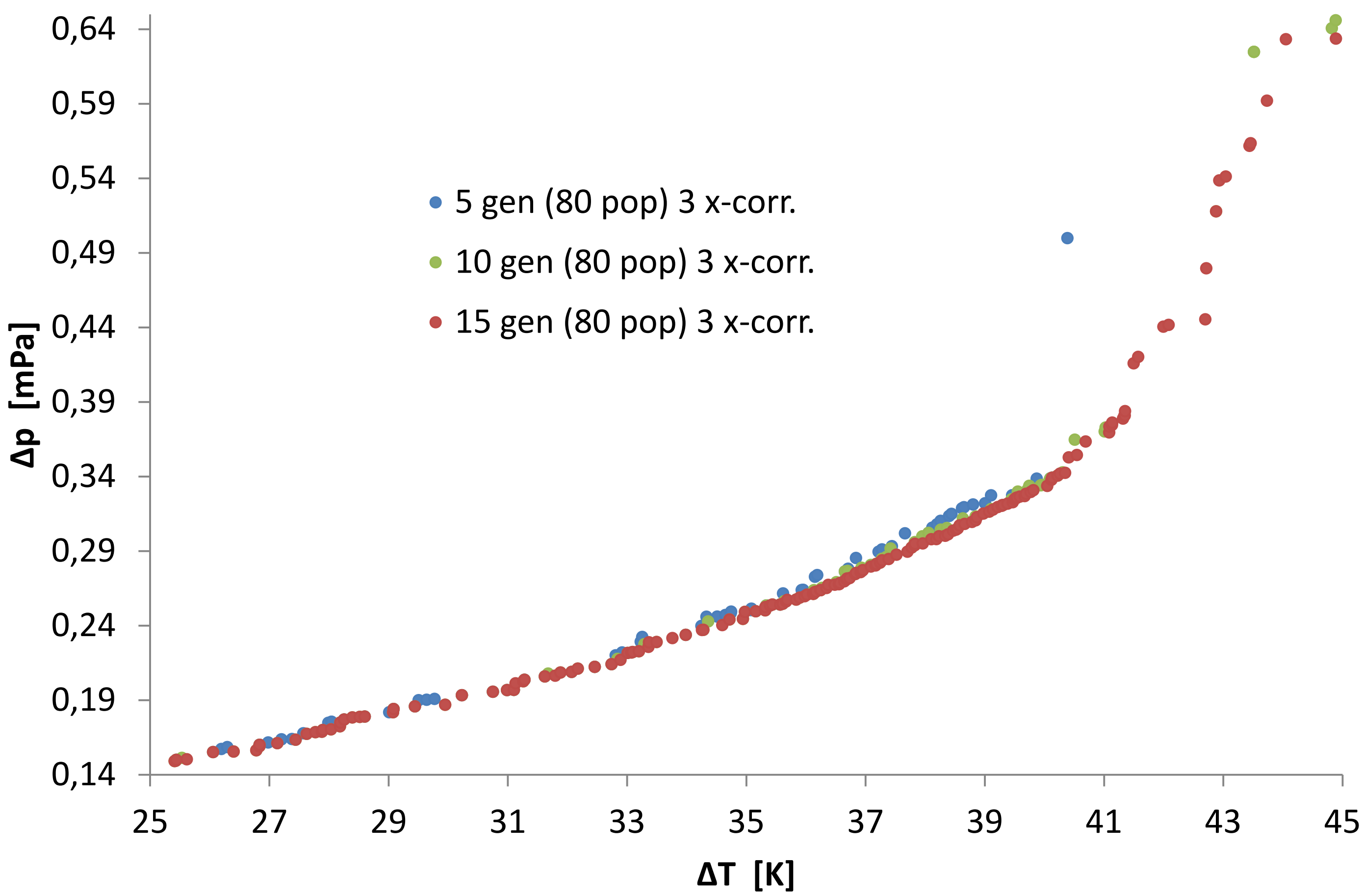
0,64
0,59
0,54
0,49
0,44
0,39
0,34
0,29
0,24
0,19
0,14
Δp [mPa]
25
27
29
31
33
35
37
39
41
43
45
ΔT [K]
20 gen (40 pop) 3 x-corr.
10 gen (80 pop) 3 x-corr.

Results



0,64
0,59
0,54
0,49
0,44
0,39
0,34
0,29
0,24
0,19
0,14
Δp [mPa]
25
27
29
31
33
35
37
39
41
43
45
ΔT [K]
20 gen (60 pop) 3 x-corr.
15 gen (80 pop) 3 x-corr.

Results



0,64
0,59
0,54
0,49
0,44
0,39
0,34
0,29
0,24
0,19
0,14
Δp [mPa]
25
27
29
31
33
35
37
39
41
43
45
ΔT [K]
5 gen (80 pop) 3 x-corr.
10 gen (80 pop) 3 x-corr.
15 gen (80 pop) 3 x-corr.

Work in progress and in the future

In progress:

- Uncertainty quantification
- Robustness evaluation of the optimal points

In the future:

- Workflow for obtaining pareto front using the single objective algorithms
- Optimization with gradient based methods

Thank you!