Advances in Evolutionary Multi-objective Optimization: Algorithms, Issues and Applications

A/P Kay Chen TAN
Department of Electrical and Computer Engineering
National University of Singapore
Outline of Talk

1. What is an Evolutionary Algorithm?
2. A brief review of MOEA
3. Issues and advanced features
4. Performance assessments
5. Software and applications
6. Future developments
Introduction

- Evolutionary algorithm (EA) is a stochastic search technique inspired by the principles of natural selection and adaptation.
- **EA is a powerful tool for solving complex Multi-Objective (MO) optimization problems.**
  - Capable of searching for the global trade-off.
  - Robust and applicable to a wide variety of problems.
  - Capable of handling non-smooth, multi-dimensional spaces.

A minimization problem

\[
f_1(x_1, \ldots, x_n) = 1 - \exp\left(-\sum_{i=1}^{n} \left(x_i - \frac{1}{\sqrt{n}}\right)^2\right)
\]

\[
f_2(x_1, \ldots, x_n) = 1 - \exp\left(-\sum_{i=1}^{n} \left(x_i + \frac{1}{\sqrt{n}}\right)^2\right)
\]

\[n = 8 \text{ and } x_i \in [-2, 2]\]
The research potential for MOEA is high. It has grown significantly since the first MOEA proposed in 1985.

- More than 150 PhD and MSC thesis since 1995.
- More than 200 book chapters and technical reports.
The MOEA is one of the four fastest growing areas in the field of Computational Intelligence research.

One major International Conference (bi-annual) on Evolutionary Multi-criterion Optimization (EMO) dedicated for MOEA research.

2007 IEEE Symposium on Computational Intelligence in Multi-criteria Decision Making.

Special Sessions and Program Tracks of MOEA are regularly organized in major evolutionary computation conferences, such as CEC and GECCO.
Some Popular MOEAs

- Vector Evaluated Genetic Algorithm (Schaffer, 1985)
- Niched Pareto Genetic Algorithm (Horn and Nafpliotis, 1993)
- Multi-Objective Genetic Algorithm (Fonseca and Fleming, 1995)
- Pareto Archived Evolution Strategy (Knowles and Corne, 1999)
- Incrementing MOEA (Tan et al, 2001)
- Nondominated Sorting Genetic Algorithm II (Deb et al, 2002)
- Strength Pareto Evolutionary Algorithm 2 (Zitzler et al, 2001)

In MO optimization, the goal is to achieve:

- Diversity.
- Uniform distribution.
- Minimum proximity between the generated and the true Pareto front.
Handling Elements: Provide immediate usefulness for finding the non-dominated set.

- ‘Min-Max’, ‘Sub-Pop’ and others received less interest as compared to ‘Pareto’, ‘Weights’, ‘Goals’ and ‘Pref’.
- ‘Weights’ has attracted significant attention from 1985 - 2000.
- The popularity of ‘Pareto’ continues to grow significantly.
- **Supporting Elements**: Plays an indirect role in supporting the algorithm for better performance.

  - It was developed more recently than MO handling elements.
  - The distribution operator ‘Dist’ for distributing individuals along the trade-offs is very popular.
  - The ‘Elitism’ operator for preserving good solutions at each generation has been incorporated in most algorithms.
**Advanced Features in MOEAs**

- **Goal**
  - Desired value for each objective.
  - Can be used to specify design specification.
  - Strings that satisfy goal have lower (better) rank than strings that do not.

---

MOEA minimization with a feasible goal setting

Gen = 5

Gen = 70
Feasible but extreme goal setting

Infeasible goal setting

\[ f_1 \]

- Individuals with rank = 1
- Individuals with rank > 1
- goal = (0.98, 0.2)
Logical “AND” and “OR” connectives among goals

\((G_1 \cup G_2 \cup G_3 \cup G_4)\) \hspace{2cm} \((G_1 \cap G_2 \cap G_3)\)
Advanced Features

- Priority
  - Different priority for each objective.
  - Assign relative importance for each objective.
  - Between strings of equal rank, priority will be used to determine superiority.
Advanced Features

- **Soft/Hard constraints**
  - ✓ Soft: always considered
  - ✓ Hard: considered while goal not satisfied

- **Example: Process control**
  - ✓ Obj1: rise time (soft)
  - ✓ Obj2: actuator limit (hard)
$f_1$ has soft priority higher than $f_2$

Gen = 5

Gen = 70

$f_1$ has hard priority higher than $f_2$

Gen = 5

Gen = 70
Advanced Features

- MO Convergence Trace
  - Progress ratio:
    \[ Pr^{(n)} = \frac{\text{the number of nondom\_indiv}^{(n)} \text{ dominating } \text{nondom\_indiv}^{(n-1)}}{\text{the number of nondom\_indiv}^{(n)}} \]
  - Can be used as a measure of performance or stopping criteria in MO optimization.
Advanced Features

- Dynamic Population Size
  - MO optimization often requires a large population size in order to cover the entire Pareto front.
  - Population size changes according to the population distribution at each generation.
  - Start with small population for initial search.
  - Increase or decrease the population size according to the Pareto front during the evolution process.

Local Perturbation

No local perturbation for parents closed together

Local perturbation for parents apart from each other

- - - - Fuzzy neighborhood boundary
   □ Parent
   ○ Perturbed child
   - - - - - Pareto Frontier

Minimization

$f_1$

$f_2$
Adaptive Mutation Operator

- Maintains a balance between the introduction of diversity and local fine-tuning
  - Adapts a specific region of chromosome.
  - Mutation rate decreases along the evolution process.

Population size versus generation

Population distribution
Performance Assessments

- **Generational Distance (GD)**
  Measures how far the evolved solution set is from the true Pareto front.

- **Spacing (S)**
  Measures how evenly the evolved solutions distribute itself.

- **Maximum Spread (MS)**
  Measures how well the true Pareto front is covered by the evolved solution set.

Problem Test Suite

<table>
<thead>
<tr>
<th>Test Problem</th>
<th>Features</th>
</tr>
</thead>
<tbody>
<tr>
<td>ZDT1</td>
<td>Pareto front is convex.</td>
</tr>
<tr>
<td>ZDT2</td>
<td>Pareto front is non-convex.</td>
</tr>
<tr>
<td>ZDT3</td>
<td>Pareto front consists of several noncontiguous convex parts.</td>
</tr>
<tr>
<td>ZDT4</td>
<td>Pareto front is highly multi-modal where there are 21⁹ local Pareto fronts.</td>
</tr>
<tr>
<td>ZDT6</td>
<td>The Pareto optimal solutions are non-uniformly distributed along the global Pareto front. The density of the solutions is low near the Pareto front and high away from the front.</td>
</tr>
</tbody>
</table>
Problem Test Suite

<table>
<thead>
<tr>
<th>Test Problem</th>
<th>Features</th>
</tr>
</thead>
<tbody>
<tr>
<td>6 FON</td>
<td>Pareto front is non-convex.</td>
</tr>
<tr>
<td>7 KUR</td>
<td>Pareto front consists of several noncontiguous convex parts.</td>
</tr>
<tr>
<td>8 POL</td>
<td>Pareto front and Pareto optimal solutions consist of several noncontiguous convex parts.</td>
</tr>
<tr>
<td>9 TLK</td>
<td>Noisy landscape.</td>
</tr>
<tr>
<td>10 TLK2</td>
<td>Non-stationary environment.</td>
</tr>
</tbody>
</table>
Comparative Study

Generational Distance

- Non-elitist algorithms, such as VEGA and MOGA have weak convergence properties.
- VEGA, MOGA and NPGA are affected severely by noise.
- IMOEA, NSGAII and SPEA2 are generally competitive in terms of GD.

Spacing

- CCEA and IMOEA give the best values of S for almost all the test problems.
- NSGAII and SPEA2 also give excellent performance in terms of the population distribution.
- PAES is less competitive for most test problems.
Comparative Study

Maximum Spread

- NSGAII and SPEA2 give the best performance in terms of variance and consistency.
- The performance of CCEA is shown to be superior for ZDT4.
- IMOEA produces excellent results except for ZDT4 and TLK.
A Distributed Evolutionary Algorithm Framework

- An infrastructure supporting distributed evolutionary computing using existing Internet and hardware resources.

- Developed upon the technology of Java 2 platform of Enterprise Edition (J2EE).
- Exploit the inherent parallelism of evolutionary algorithms.
- Incorporates the features of robustness, security, and workload balancing.

Distributed Cooperative Coevolutionary Algorithm

- Decomposes complex problem into smaller problems via co-evolving subpopulations cooperatively
  - Divide-and-Conquer Strategy.
  - Each subpopulation evolves a different decision variable.
  - Fitness is dependent on the collaboration between each subpopulation.

- **Parallelization Strategy**

  - Coarse-grained parallelization strategy.
  - Subpopulations are partitioned into a number of groups and assigned to peer computers.
  - Indirect cooperation is achieved through the exchange of archive and representatives between peers and a central server.
  - Peers are synchronized at fixed intervals to ensure better cooperation.
**11 PCs in LAN**

<table>
<thead>
<tr>
<th>PC</th>
<th>Configuration CPU (MHz)/RAM (MB)</th>
</tr>
</thead>
<tbody>
<tr>
<td>server</td>
<td>PIV 1600/512</td>
</tr>
<tr>
<td>peer 1</td>
<td>PIII 800/ 512</td>
</tr>
<tr>
<td>peer 2</td>
<td>PIII 800/ 512</td>
</tr>
<tr>
<td>peer 3</td>
<td>PIII 800/ 256</td>
</tr>
<tr>
<td>peer 4</td>
<td>PIII 933/384</td>
</tr>
<tr>
<td>peer 5</td>
<td>PIII 933/128</td>
</tr>
<tr>
<td>peer 6</td>
<td>PIV 1300/ 128</td>
</tr>
<tr>
<td>peer 7</td>
<td>PIV 1300/ 128</td>
</tr>
<tr>
<td>peer 8</td>
<td>PIII 933/ 512</td>
</tr>
<tr>
<td>peer 9</td>
<td>PIII 933/ 512</td>
</tr>
<tr>
<td>peer 10</td>
<td>PIII 933/256</td>
</tr>
</tbody>
</table>

**Configurations**

<table>
<thead>
<tr>
<th></th>
<th>Subpopulation size 20; archive size 100</th>
</tr>
</thead>
<tbody>
<tr>
<td>Chromosome length</td>
<td>30 bits for each variable</td>
</tr>
<tr>
<td>Selection</td>
<td>Tournament selection</td>
</tr>
<tr>
<td>Crossover operator</td>
<td>Uniform crossover</td>
</tr>
<tr>
<td>Crossover rate</td>
<td>0.8</td>
</tr>
<tr>
<td>Mutation operator</td>
<td>Bit-flip mutation</td>
</tr>
<tr>
<td>Mutation rate</td>
<td>$2/L$, where $L$ is the chromosome length</td>
</tr>
<tr>
<td>Number of evaluation</td>
<td>120,000</td>
</tr>
<tr>
<td>Exchange interval</td>
<td>5 generations</td>
</tr>
<tr>
<td>Sync. interval</td>
<td>10 generations</td>
</tr>
</tbody>
</table>
Generational Distance

Spacing

Maximum Spread

Hyper-volume Ratio
Multiobjective Evolutionary Optimization: Algorithms and Applications

Observation

- Effective in reducing simulation runtime without sacrificing performance.
- Speedup achievable is more significant for large problems.
- The increased communication cost counteracts the reduction of computation cost with increasing number of peers.

<table>
<thead>
<tr>
<th>Number of peers</th>
<th>ZDT1</th>
<th>ZDT2</th>
<th>ZDT3</th>
<th>ZDT4</th>
<th>ZDT6</th>
</tr>
</thead>
<tbody>
<tr>
<td>2</td>
<td>1.52</td>
<td>1.70</td>
<td>1.47</td>
<td>1.23</td>
<td>1.01</td>
</tr>
<tr>
<td>3</td>
<td>2.01</td>
<td>1.99</td>
<td>1.88</td>
<td>1.47</td>
<td>1.11</td>
</tr>
<tr>
<td>4</td>
<td>2.25</td>
<td>2.21</td>
<td>1.95</td>
<td>1.50</td>
<td>1.14</td>
</tr>
<tr>
<td>5</td>
<td>2.48</td>
<td>2.69</td>
<td>2.15</td>
<td>1.56</td>
<td>1.14</td>
</tr>
<tr>
<td>6</td>
<td>2.81</td>
<td>3.03</td>
<td>2.83</td>
<td>1.70</td>
<td>1.29</td>
</tr>
<tr>
<td>7</td>
<td>2.87</td>
<td>3.32</td>
<td>2.77</td>
<td>1.88</td>
<td>1.25</td>
</tr>
<tr>
<td>8</td>
<td>3.38</td>
<td>3.27</td>
<td>2.92</td>
<td>1.82</td>
<td>1.26</td>
</tr>
<tr>
<td>9</td>
<td>3.46</td>
<td>3.36</td>
<td>2.96</td>
<td>1.83</td>
<td>1.26</td>
</tr>
<tr>
<td>10</td>
<td>3.46</td>
<td>3.18</td>
<td>2.79</td>
<td>1.82</td>
<td>1.25</td>
</tr>
</tbody>
</table>
MOEA Toolbox

The MOEA toolbox provides user-friendly GUI access to a powerful multi-objective evolutionary algorithm, saving decision-makers time in developing their own EA programs.

- **Main Features**
  - ✓ Niching and sharing scheme.
  - ✓ Logical “AND” and “OR” operations.
  - ✓ MO convergence trace & dynamic population size.
  - ✓ Simple constraint handling & interactive GUIs.

Layout of MOEA Toolbox

Quick Setup

Remote Control

Population Handling

Master Window

Simulation Objectives

Graphical Results
Role of MOEA Toolbox

The Role of MOEA Toolbox in the Optimization Process:

1. **Real World System**
   - Specifications

2. **Data File**
   - text file

3. **Model**
   - MOEA Toolbox
   - Evaluation
   - Evolution
   - Random Initial Population
   - Population of Strings

4. **Parameters**

5. **Plots & Results**
Application: Hard Disk Drive Servo

- Hard Disk Drive Servo Specifications
  - The control input should not exceed $\pm 2$ volts due to physical constraints on the actual actuator.
  - The overshoots and undershoots of the step response should be kept less than 5% as the R/W head can start to read or write within $\pm 5\%$ of the target.
  - The 5% settling time in the step response should be less than 2 milliseconds.
  - Excellent steady-state accuracy.
  - Robust in terms of disturbance rejection and uncertainty.

# Time domain and frequency domain design specifications

<table>
<thead>
<tr>
<th>Frequency Domain</th>
<th>Objective</th>
<th>Goal</th>
</tr>
</thead>
<tbody>
<tr>
<td>1. Stability (Closed-loop poles)</td>
<td>$\text{Nr}([\text{eig}(A_{clp})] &gt; 0)$</td>
<td>0</td>
</tr>
<tr>
<td>2. Closed-loop sensitivity or Disturbance rejection</td>
<td>$\bar{\sigma}[S(j\omega)]$</td>
<td>1</td>
</tr>
<tr>
<td>3. Plant uncertainty</td>
<td>$\bar{\sigma}[T(j\omega)]$</td>
<td>1</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Time Domain</th>
<th>Objective</th>
<th>Goal</th>
</tr>
</thead>
<tbody>
<tr>
<td>4. Actuator saturation</td>
<td>Max($u$)</td>
<td>2 volts</td>
</tr>
<tr>
<td>5. Rise time</td>
<td>$T_{\text{rise}}$</td>
<td>2 milli sec</td>
</tr>
<tr>
<td>6. Overshoots</td>
<td>$O_{\text{shoot}}$</td>
<td>0.05</td>
</tr>
<tr>
<td>7. Settling time</td>
<td>$5% T_{\text{settling}}$</td>
<td>2 milli sec</td>
</tr>
<tr>
<td>8. Steady-state error</td>
<td>$SS_{\text{error}}$</td>
<td>0</td>
</tr>
</tbody>
</table>

\[ y(n) = Cx(n) + Du(n) \]
\[ x(n+1) = Ax(n) + Bu(n) \]
Evolutionary HDD Servo System Design
Design Trade-off Graph

Progress Ratio
Servo Output Response

- Evolutionary 2DOF Controller
- RPT Controller
- PID Controller

Disturbance Rejection

- Disturbance input
- Evolutionary 2DOF Controller
- RPT Controller
- PID Controller
Response to Change in Resonant Frequency

\[ \omega_n = 14.82 \text{ kHz} \]

\[ \omega_n = 7.41 \text{ kHz} \]
Real-time Implementation
Application: Vehicle Routing Problem with Time Windows

VRPTW is an MO optimization problem: the number of vehicles and routing cost can be minimized concurrently, subject to time window capacity constraints.

- VRPTW Specifications
  - Every vehicle must start and end its route at the depot.
  - Each vehicle and route has a capacity limit.
  - All vehicles are constrained by an arrival time window for customers and depot.

An Example of Vehicle Routing Solution
**Features...**

- **Multiple objectives**
  - ✔ Travel distance
  - ✔ Number of vehicles

- **Variable-length chromosome**
  - ✔ Encodes the number of routes/vehicles and the customers served by these vehicles.
  - ✔ Every chromosome can have a different number of routes.
  - ✔ Each route is not constant but a sequence of customers to be served.

A chromosome encodes a complete routing solution.

Each route contains a sequence of customers.
Features...

- Route-exchange crossover
  - Allows good sequence of routes to be shared.
  - Infeasibility after the change can be eradicated easily.
  - Cost of each route can be computed easily.
- **Solomon’s 56 Benchmark Problems**
  - Used extensively for benchmarking.
  - Consist of 56 data set.
  - Vary in vehicle capacity, time window density, distribution of customers, etc.
  - Divided into six categories based on customer’s location and time windows.
Convergence Trace

Routing Result for RC2-07
Comparison of population distribution in the objective domain (CR along y-axis vs. NV along x-axis) for different optimization criteria of CR, NV, and MO.

<table>
<thead>
<tr>
<th>Category</th>
<th>Objective space covered by scattering points (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>CR</td>
</tr>
<tr>
<td>C_{2-04}</td>
<td>17.00</td>
</tr>
<tr>
<td>R_{1-07}</td>
<td>19.05</td>
</tr>
<tr>
<td>R_{2-07}</td>
<td>11.11</td>
</tr>
<tr>
<td>R_{C1-07}</td>
<td>24.00</td>
</tr>
<tr>
<td>R_{C2-07}</td>
<td>14.76</td>
</tr>
</tbody>
</table>
Performance Comparison

Average Simulation Time

- **Performance Comparison**
  - Categories: C1, C2, R1, R2, RC1, RC2
  - Components: CR, NV, MO

- **Average Simulation Time**
  - Categories: C1, C2, R1, R2, RC1, RC2
  - Values range from 0 to 90,000
### Performance comparison between different heuristics and MOEA

<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>$C_1$</td>
<td>10.00</td>
<td>10.00</td>
<td>10.00</td>
<td>10.00</td>
<td>10.00</td>
<td>10.00</td>
<td>10.00</td>
<td>10.00</td>
<td>10.00</td>
</tr>
<tr>
<td></td>
<td>838.00</td>
<td>828.45</td>
<td>828.38</td>
<td>828.94</td>
<td>833.32</td>
<td>851.96</td>
<td>841.96</td>
<td>832.13</td>
<td>827.00</td>
</tr>
<tr>
<td>$C_2$</td>
<td>3.00</td>
<td>3.00</td>
<td>3.00</td>
<td>3.00</td>
<td>3.00</td>
<td>3.20</td>
<td>3.00</td>
<td>3.00</td>
<td>3.00</td>
</tr>
<tr>
<td></td>
<td>589.90</td>
<td>590.30</td>
<td>591.42</td>
<td>589.93</td>
<td>593.00</td>
<td>620.12</td>
<td>611.2</td>
<td>589.86</td>
<td>590.00</td>
</tr>
<tr>
<td>$R_1$</td>
<td>12.60</td>
<td>12.25</td>
<td>12.17</td>
<td>12.50</td>
<td>11.92</td>
<td>12.58</td>
<td>12.30</td>
<td>12.91</td>
<td>12.16</td>
</tr>
<tr>
<td></td>
<td>1296.83</td>
<td>1216.70</td>
<td>1204.19</td>
<td>1268.42</td>
<td>1222.12</td>
<td>1203.32</td>
<td>1220.0</td>
<td>1205.0</td>
<td>1211.55</td>
</tr>
<tr>
<td></td>
<td>12.92</td>
<td>1187.0</td>
<td>12.16</td>
<td>12.50</td>
<td>12.17</td>
<td>12.30</td>
<td>12.30</td>
<td>12.25</td>
<td>1135.00</td>
</tr>
<tr>
<td>$R_2$</td>
<td>3.00</td>
<td>3.00</td>
<td>3.00</td>
<td>3.00</td>
<td>3.00</td>
<td>3.18</td>
<td>4.40</td>
<td>5.00</td>
<td>3.51</td>
</tr>
<tr>
<td></td>
<td>1117.70</td>
<td>995.38</td>
<td>986.32</td>
<td>1055.90</td>
<td>975.12</td>
<td>951.17</td>
<td>985.69</td>
<td>929.6</td>
<td>951.0</td>
</tr>
<tr>
<td>$RC_1$</td>
<td>12.10</td>
<td>11.88</td>
<td>11.88</td>
<td>12.25</td>
<td>11.5</td>
<td>12.75</td>
<td>13.30</td>
<td>12.60</td>
<td>12.74</td>
</tr>
<tr>
<td></td>
<td>1446.20</td>
<td>1367.51</td>
<td>1397.44</td>
<td>1396.07</td>
<td>1389.58</td>
<td>1382.06</td>
<td>1366.62</td>
<td>1392.3</td>
<td>1418.77</td>
</tr>
<tr>
<td></td>
<td>12.74</td>
<td>1355.0</td>
<td>12.25</td>
<td>13.30</td>
<td>13.25</td>
<td>1132.79</td>
<td>1108.50</td>
<td>1080.10</td>
<td>1170.93</td>
</tr>
<tr>
<td>$RC_2$</td>
<td>3.40</td>
<td>3.38</td>
<td>3.25</td>
<td>3.25</td>
<td>3.25</td>
<td>3.75</td>
<td>5.20</td>
<td>5.80</td>
<td>4.25</td>
</tr>
<tr>
<td></td>
<td>1360.60</td>
<td>1165.62</td>
<td>1229.54</td>
<td>1308.31</td>
<td>1128.38</td>
<td>1132.79</td>
<td>1108.50</td>
<td>1080.10</td>
<td>1170.93</td>
</tr>
<tr>
<td></td>
<td>3.37</td>
<td>1067.00</td>
<td>4.25</td>
<td>5.20</td>
<td>5.80</td>
<td>1132.79</td>
<td>1108.50</td>
<td>1080.10</td>
<td>1170.93</td>
</tr>
<tr>
<td>All</td>
<td>422</td>
<td>416</td>
<td>411</td>
<td>423</td>
<td>405</td>
<td>432</td>
<td>470</td>
<td>471</td>
<td>441</td>
</tr>
<tr>
<td></td>
<td>62572</td>
<td>57993</td>
<td>58502</td>
<td>60651</td>
<td>57710</td>
<td>57265</td>
<td>57903</td>
<td>56931</td>
<td>58476</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>56262</td>
</tr>
</tbody>
</table>
Future Directions

- Application of MOEAs to solve more real-world problems, such as robotics, multi-agents, etc.
- Empirical assessment of MOEA can only reveal new insights to algorithmic behaviors and performance if adequate analysis is made.
  - It is not an easy task...
    - Unifying a set of performance metrics leaving no ambiguity about effectiveness of the algorithm.
    - Presenting a framework for proper empirical assessment, e.g., practical problems.
Future Directions

- Researchers are facing the challenge of increasing dimensionality and computational cost of today’s applications.

- Design of more effective EA mechanisms
  - Improving Representation.
  - Adaptive Variation Operators.

- Handling of high-dimensional problems
  - Use of dimensional reduction techniques.
  - Use of learning techniques to gain information on the shape and position of Pareto front/set.
Future Directions

- The number of function evaluations involved in the evolutionary optimization process may be cost prohibitive or impractical.

- Via high performance computing resources
  - MOEA based upon grid-computing framework.
  - Exploit distributed computing over Internet.
  - Integration of meta-models into MOEAs.
  - Reducing the complexity of algorithms.
Not Just a Solution...

Further information: