TIEJ601, Postgraduate Seminar in Information Technology

New Mutation Operator for Multi-objective Optimization with Differential Evolution

by

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http://users.jyu.fi/~kasindhy/Welcome.html

08-03-2010

Overview

- Status of my PhD
- Thesis in a nutshell
- Background
- Polynomial mutation operator
- Tests
- Conclusion and future work

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  - *Two journal articles in review*
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  - *One article*
- ***Future***
  - *One article by June 2010*

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Thesis in a Nutshell

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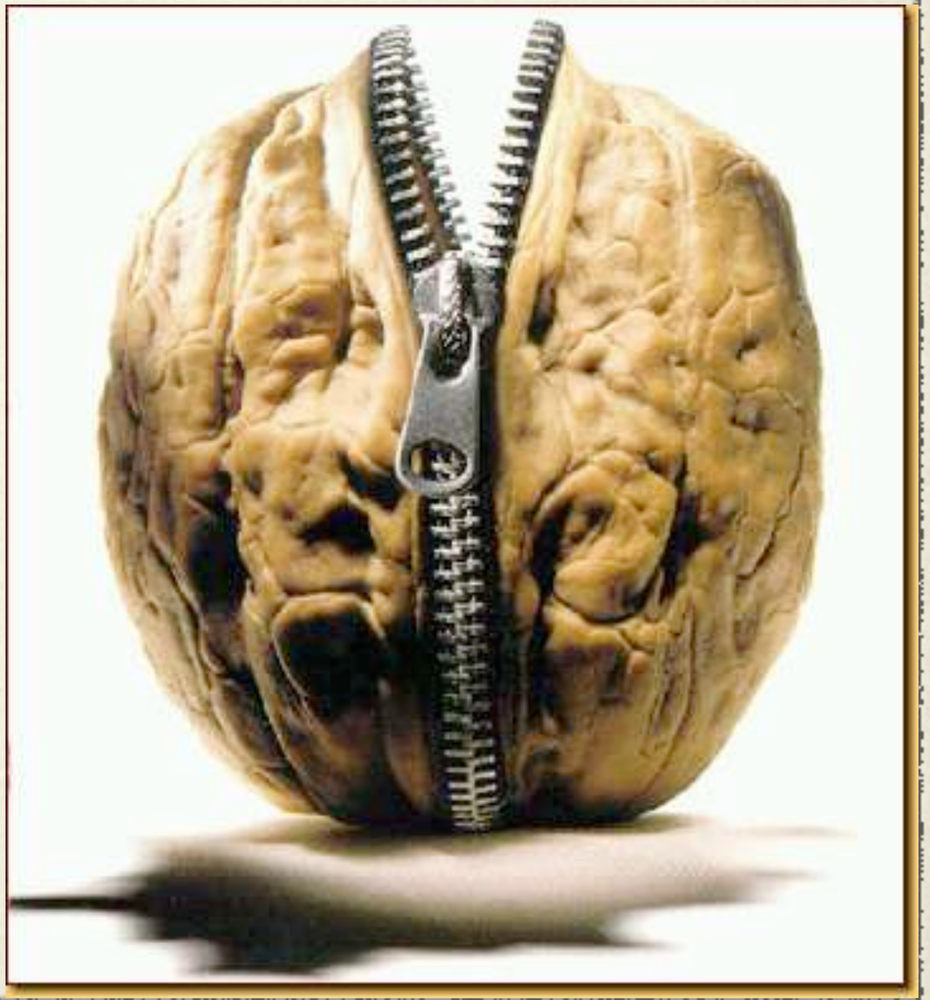

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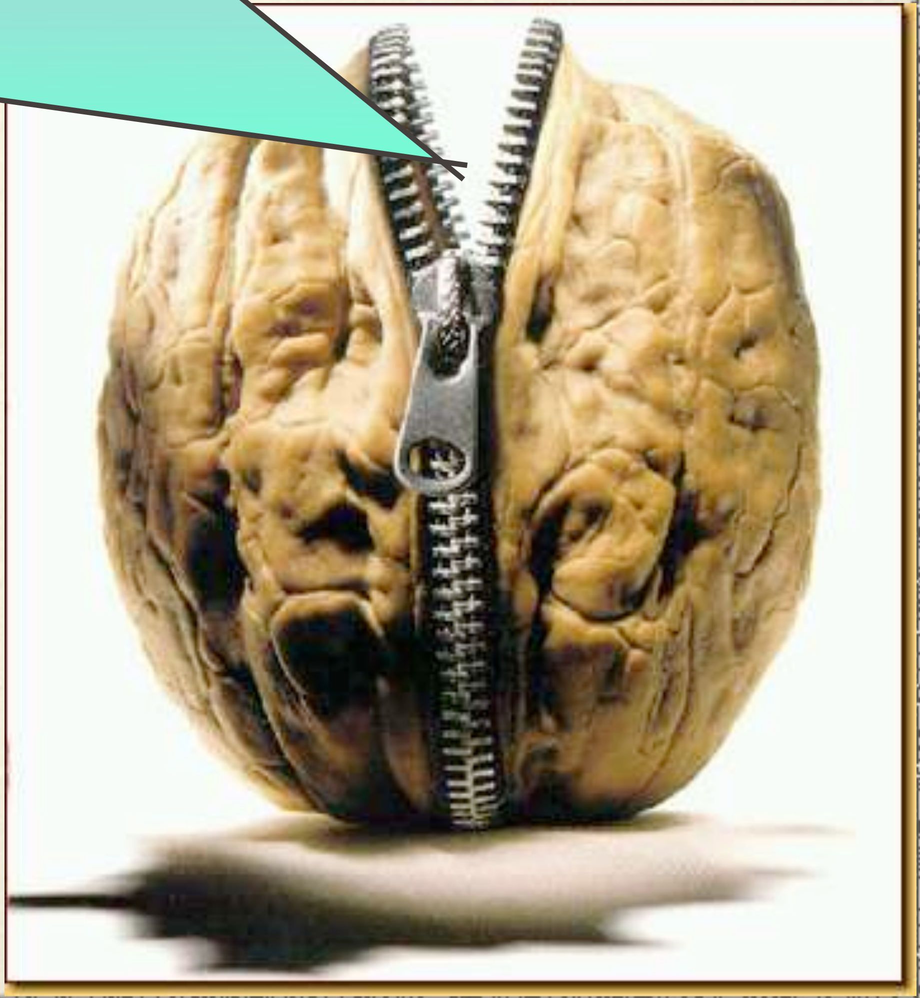
- *Principle Background:*
    - *Use MCDM techniques to speed up EMO algorithms without compromising on diversity.*



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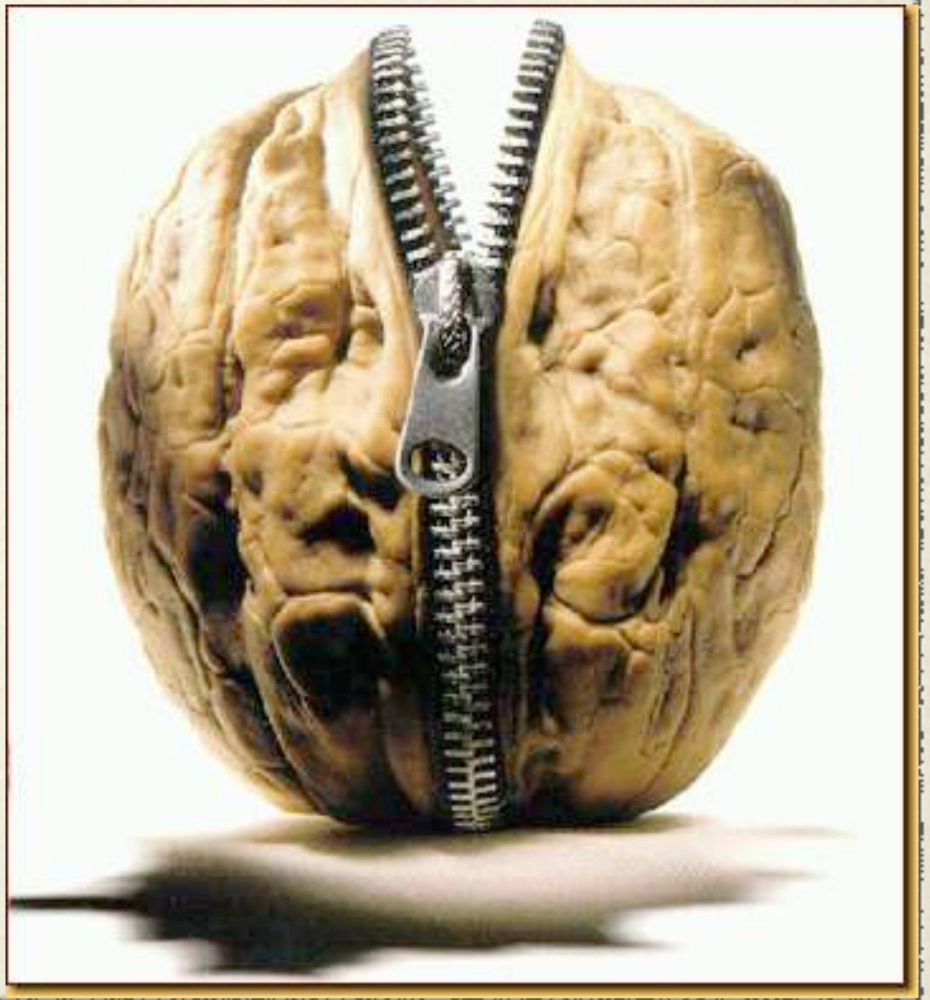

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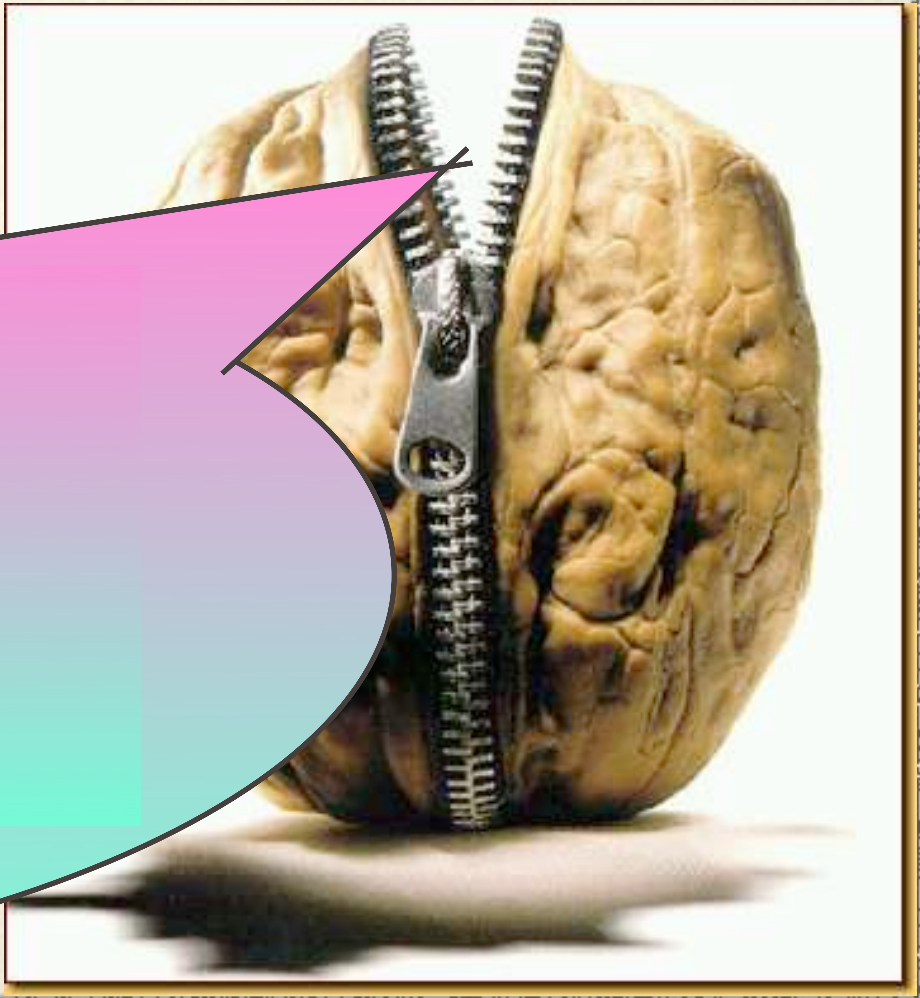

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  - *Hybrid EMO algorithm*
    - *Enhanced convergence*
    - *Good lateral diversity preservation*
    - *Stopping criteria*
    - *Wide applicability*

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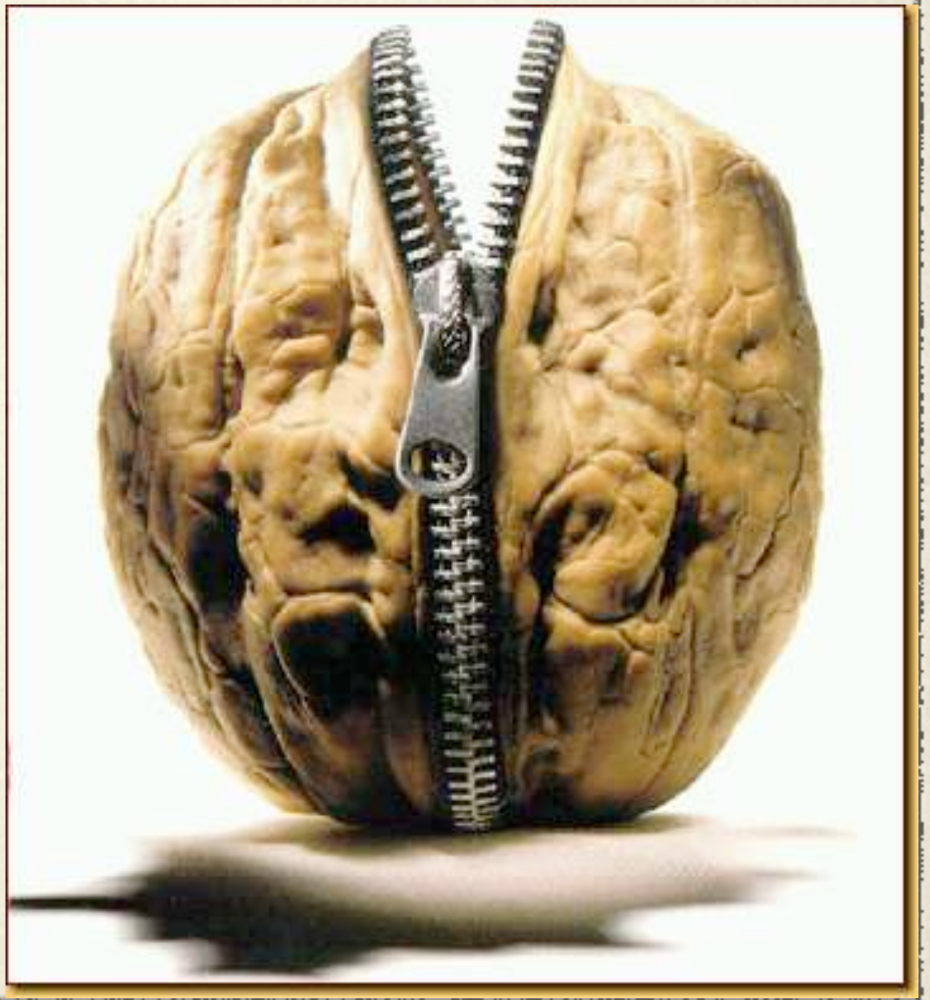

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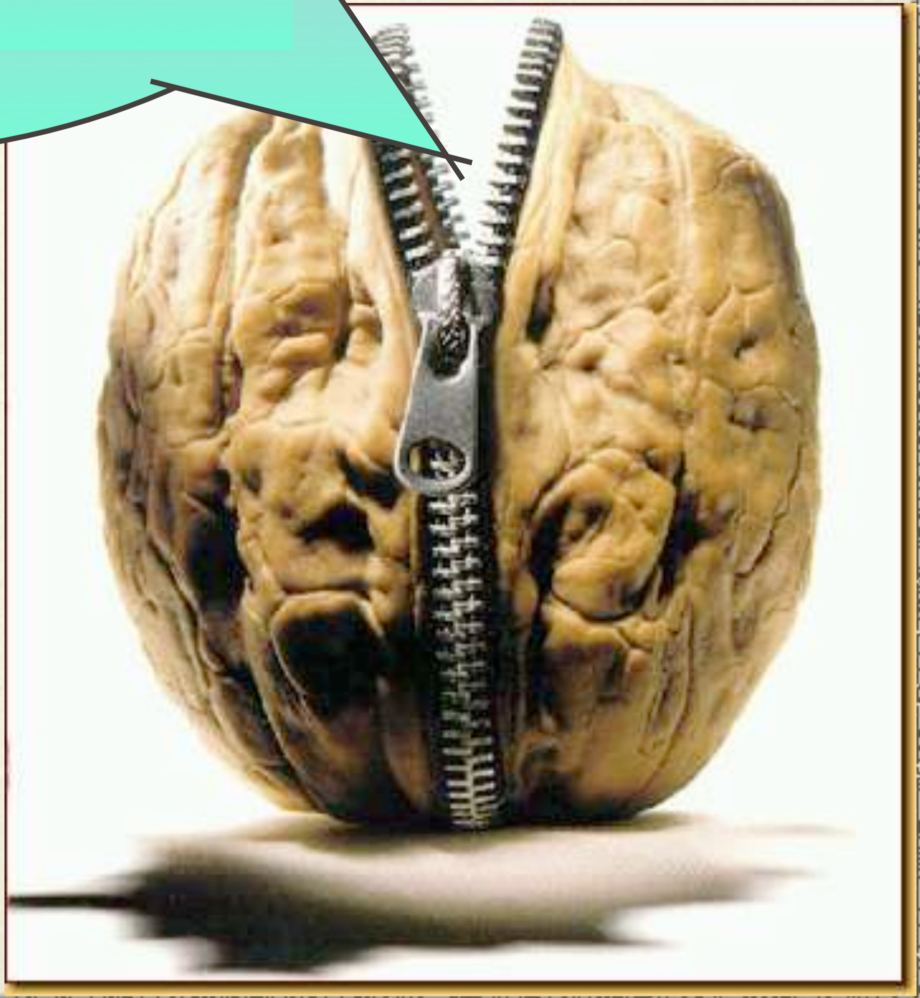
- ***Hybrid Algorithm:***
  - ***Efficient operators***
  - ***Good diversity preservation***
  - ***Efficient local search procedure***



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- *EMO Algorithm:*
  - *Initialize population*
  - *Fitness evaluations*
  - **Recombination**
  - **Mutation**
  - *Selection*

- Evolutionary Multi-objective Optimization (EMO) algorithms - widely used in multi-objective optimization.
- Numerous versions of different EMO algorithms have been proposed.
  - Fewer research on operators for EMO algorithms.
  - Single objective operators usually borrowed as such in multi-objective algorithms.

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- EMO algorithm - Differential Evolution
  - Widely used algorithm in the field of single and multi-objective optimization.
  - Simple, self-adapting mutation operator.
  - Trial vector is generated by adding scaled random vector difference to a third vector.
  - Exploits linear dependencies between decision variables.
- Real-life multi-objective problems may not necessarily have linear dependencies in decision variables.

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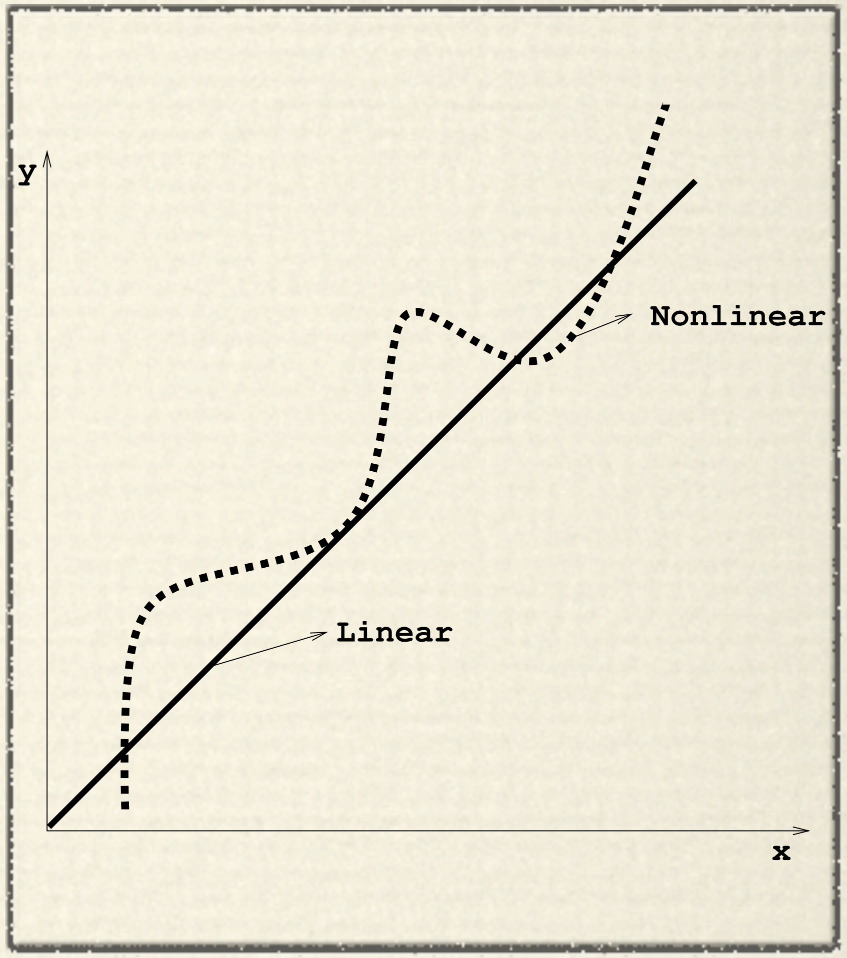

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Polynomial Mutation Operator (POMO)

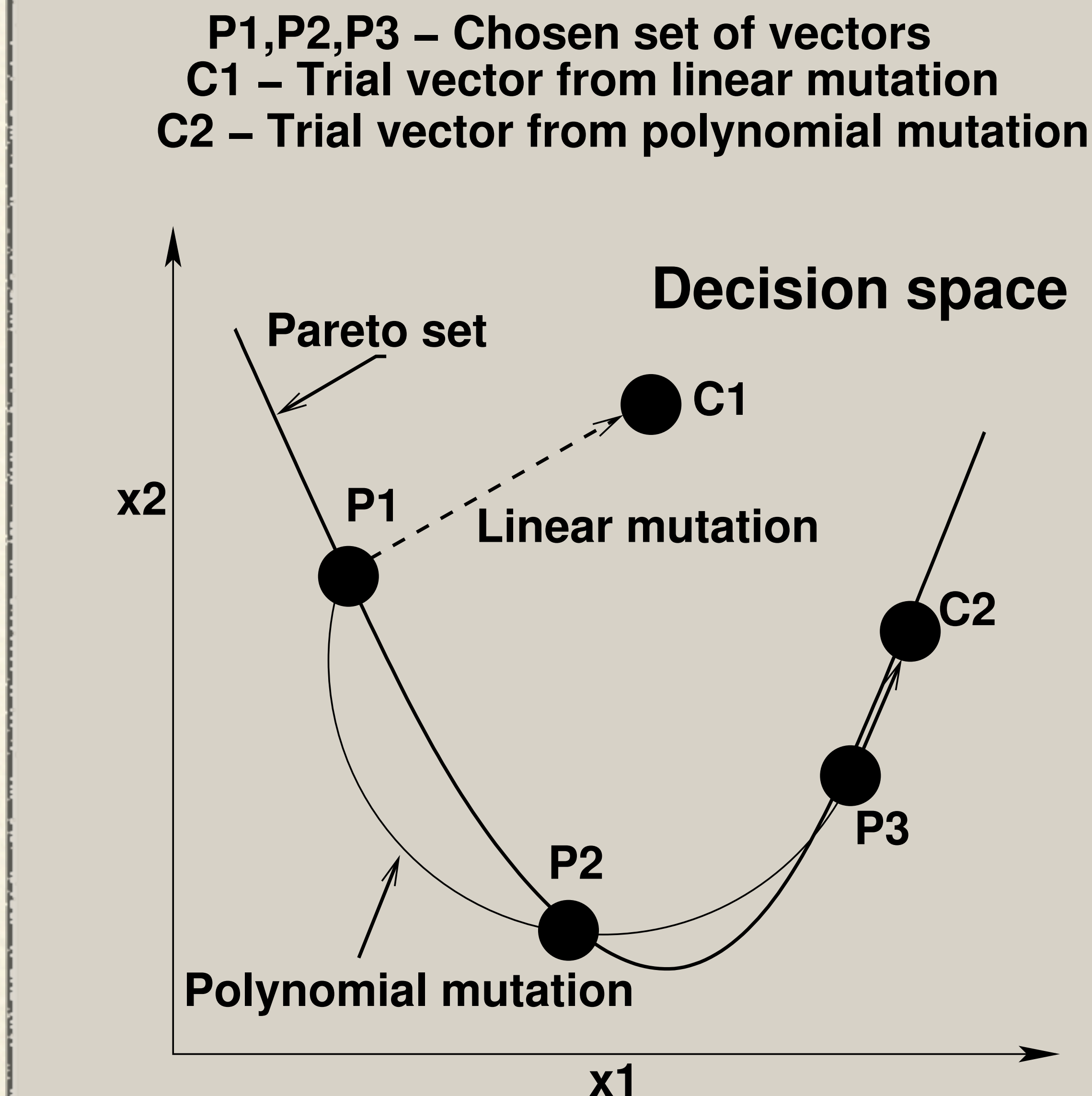
- Operator based on polynomials:

$$p_i(t) = c^i_{m-1}t^{m-1} + c^i_{m-2}t^{m-2} + \ldots + c^i_0$$

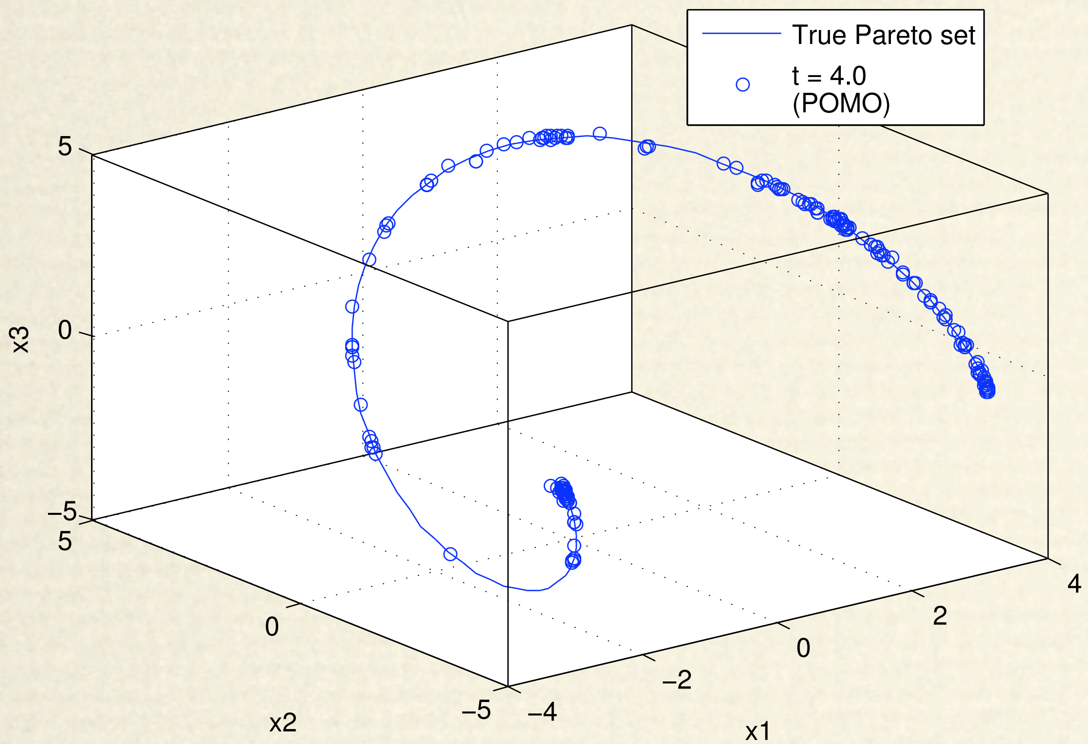
degree	name	coefficients
0	constant	$c^i_0 = x^1_i$
1	linear	$c^i_0 = x^1_i$ $c^i_1 = x^2_i - x^1_i$
2	quadratic	$c^i_0 = x^1_i$ $c^i_1 = \frac{1}{2}(-3x^1_i + 4x^2_i - x^3_i)$ $c^i_2 = \frac{1}{2}(x^1_i - 2x^2_i + x^3_i)$
3	cubic	$c^i_0 = x^i_1$ $c^i_1 = \frac{1}{6}(-11x^1_i + 18x^2_i - 9x^3_i + 2x^4_i)$ $c^i_2 = \frac{1}{2}(2x^1_i - 5x^2_i + 4x^3_i - x^4_i)$ $c^i_3 = \frac{1}{6}(-x^1_i + 3x^2_i - 3x^3_i + x^4_i)$

- Original DE mutation operator:

$$V_{i,G+1} = X_{r_3,G} + F \cdot (X_{r_1,G} - X_{r_2,G})$$

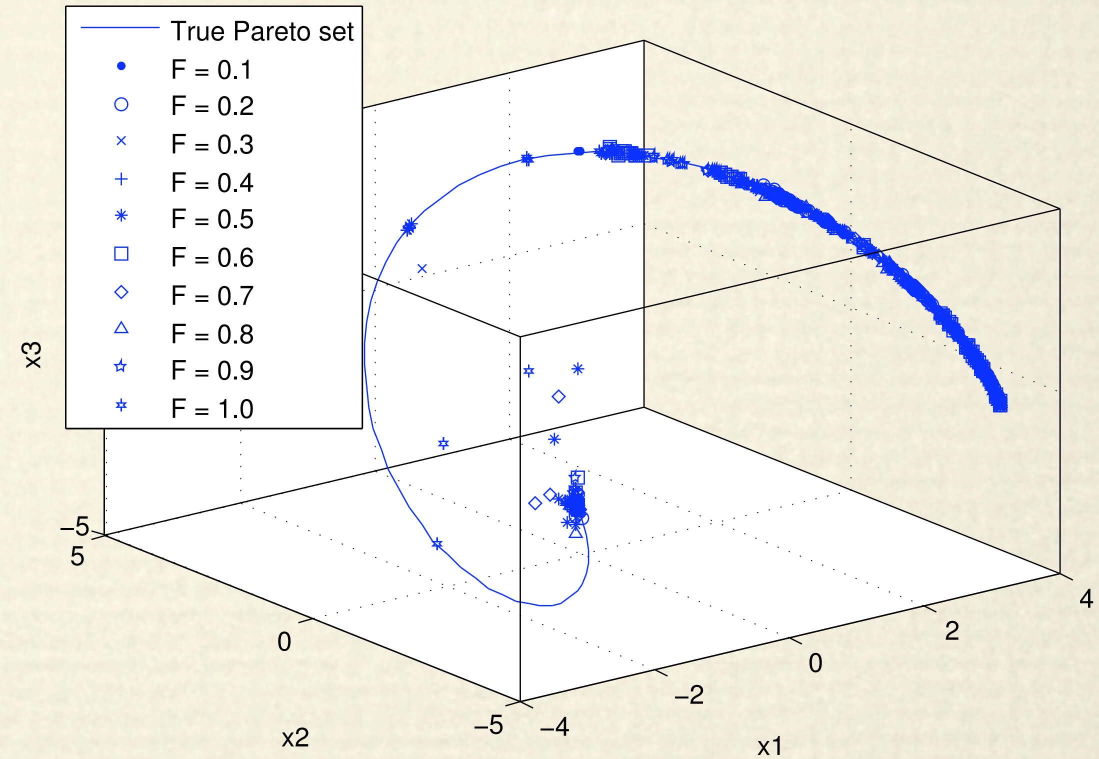


Tests



- *Polynomial mutation*

- *EMO algorithm - GDE3*
- *Test problems - OKA2*
    - *Bi-objective, 3 variables*



- *Linear mutation*

Tests

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COMPARISON OF THE HYPERVOLUMES FOR THE ORIGINAL AND POLYNOMIAL MUTATION APPROACHES (LARGER VALUE IS BETTER).

Test Problem	Starting population for comparison			Original mutation operator			Polynomial mutation operator		
	Best	Median	Worst	Best	Median	Worst	Best	Median	Worst
ZDT3	0.5552	0.5514	0.5491	0.5671	**0.5659**	0.5631	0.5573	0.5548	0.5524
ZDT4	0.7623	0.6554	0.1661	0.7651	**0.7631**	0.16666	0.7638	0.7560	0.1661
OKA1	0.7024	0.6970	0.6847	0.7038	**0.6992**	0.6922	0.7024	0.6978	0.6899
OKA2	0.6668	0.4907	0.4112	0.6676	0.4944	0.4144	0.6701	**0.5115**	0.4286
WFG9	0.4232	0.4216	0.4216	0.4236	**0.4224**	0.4198	0.4239	**0.4220**	0.4192
UF2	0.7511	0.7472	0.7450	0.7516	0.7472	0.7450	0.7516	**0.7490**	0.7468
UF4	0.4852	0.4840	0.4819	0.4872	0.4862	0.4841	0.48832	**0.4871**	0.4846

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- Linear mutation works better on problems with linear dependencies.
- Polynomial mutation handles problems with nonlinear dependencies better.

Conclusion & Future Work

- Conclusion
  - Polynomial operator demonstrates the need for a better operator to handle non-linear variable dependencies.
- Future Work
  - Choice of t-value requires further study.
  - Hybrid algorithm of linear and non-linear mutation operators.

Colleagues

- Tomi Haanpää
- Sauli Ruuska

Thank you