BRNO FACULTY OF ELECTRICAL UNIVERSITY ENGINEERING OF TECHNOLOGY AND COMMUNICATION



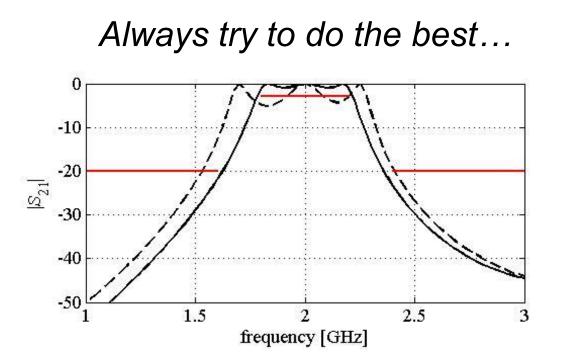
#### Evolutionary Optimization in Electromagnetics

COST IC 1407 Workshop, Bratislava, 5.4.2017

## Outline

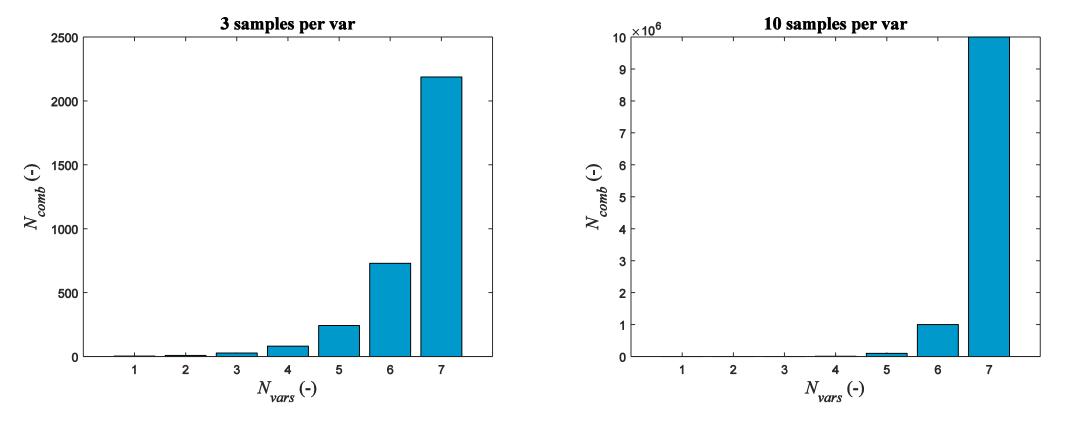
- Optimization fundamentals
- Local vs. global methods
- Evolutionary algorithms
- Genetic Algorithms
- Particle Swarm Optimization
- Multi-objective optimization
- Examples in FOPS

#### Motivation



#### **Motivation**



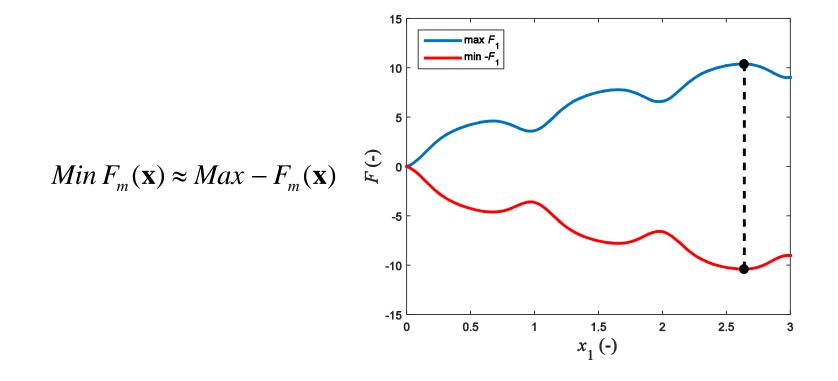


## Optimization

Choice of the best variant from available optionsIn mathematics:

 $\begin{array}{ll} Minimize & F_{m}(\mathbf{x}), & m = 1, 2, ..., M, \\ subject to & g_{j}(\mathbf{x}) \geq 0, \ j = 1, 2, ..., J, \\ x_{n,\min} \leq x_{n} \leq x_{n,\max}, & n = 1, 2, ..., N. \end{array}$ 

#### Min vs. Max

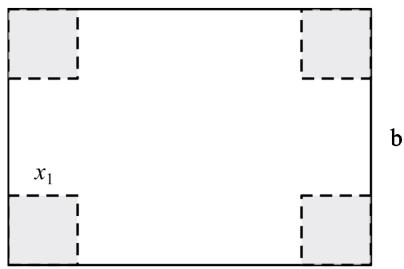


## **Objective formulation**

#### **Problem:**

Having sheet of paper with dimensions *a* and *b*, what is the size of squares to be cut from the corners of the sheet to build a box with the highest volume?

Decision space:  $\mathbf{x} = [x_1]$ Objective space  $f_1 = 4x_1^3 - (2a + 2b)x_1^2 + abx_1$ 

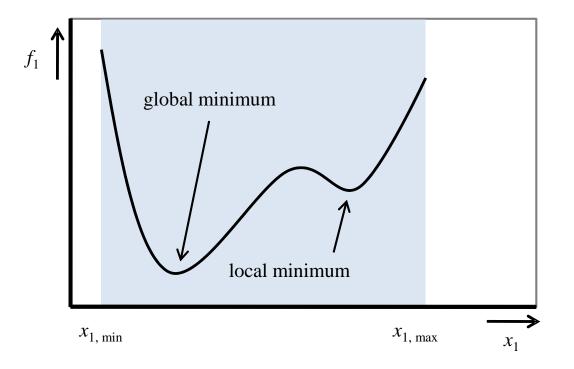


#### **Optimization taxonomy**



SOO (Single-Objective)MOO (Multi-Objective)Single variableMultiple variablesGlobalLocalContinuous dec. spaceDiscrete dec. spaceUnconstrainedConstrainedStaticDynamic

#### Global vs. local minimum



#### Global vs. Local

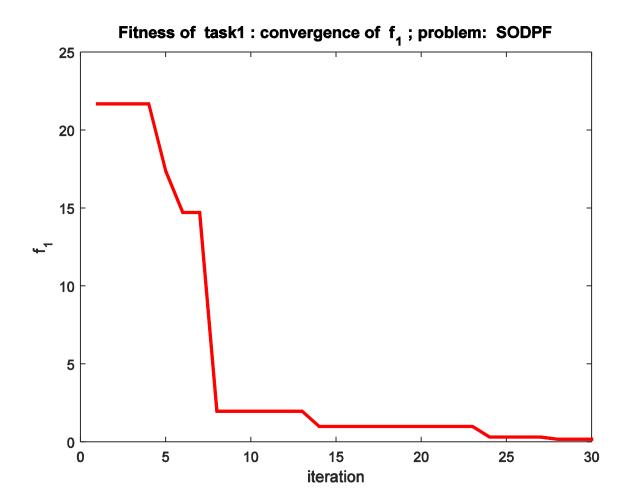
 local methods are faster and more efficient, but global are more robust, no dependence on initial guess

- derivatives can not be evaluated,
- objective functions cannot be formulated in closed form (e.g. use of solver output),
- initial guess is too far,
- user is lazy!

## **Evolutionary methods**

- random start choice of the initial guess is not so important
- agent (individual, ...) updates its position within the decision space
- agents are able to escape from local minimum (maximum)
- stochastic different runs different results (at least development)

### Convergence plot



### Genetic algorithms

#### Holland 1962

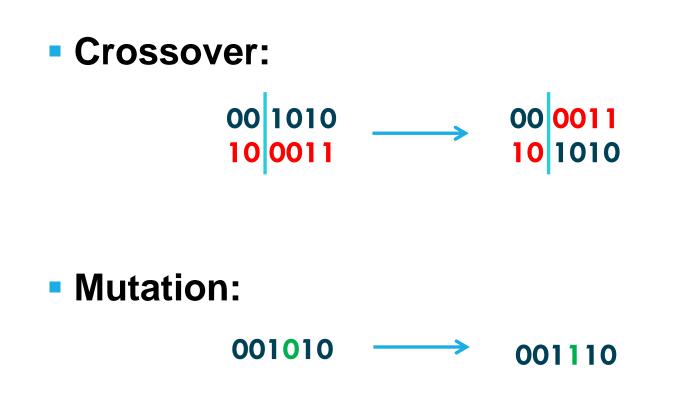
 Inspired by Darwin – only good properties of genome are maintained for next generations

#### GAs work with discrete decision space!!!

## GA - taxonomy

- Gene variable coded in binary form
- Gene length number of bits used for decoding
- Chromosome genes from all variables
- Generation multiple chromosomes
- Decimation reduction of the worst Chromosomes in Generation
- Mating pool set of Chromosomes selected for reproduction
- Crossover combination of two Chromosomes
- Mutation bit change in one Chromosome

#### GA - reproduction



## GA - reproduction

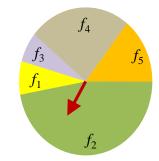
Decimation:	g <sub>1</sub>	<b>g</b> <sub>2</sub>	g <sub>3</sub>	f
	110	0101	00010	0,15
	101	1101	00101	0,36
	011	1011	00110	1,53
	100	1010	10001	6,27
	011	0011	11010	11 ,83
	101	1011	10010	13 ,21
	100	0101	00101	20,89
	011	0101	10101	56 ,12

#### Elitism:

 Solution with the best value of objective function is automatically considered also for the next generation.

### GA - reproduction

#### Roulette selection:



#	f(-)	1/f(-)	%
1	6.82	0.15	7.80
2	1.11	0.90	47.94
3	8.48	0.12	6.28
4	2.57	0.39	20.71
5	3.08	0.32	17.28
total	22.06	1.88	100.00

Tournament selection:

f	Chrom.	Round	Mating pool
1.25	<b>C</b> 1	C1 vs. C2	<b>C</b> 1
7.37	<b>C2</b>	C4 vs. C2	<b>C4</b>
2.42	C3	<b>C1</b> vs. C3	<b>C</b> 1
6.12	<b>C4</b>	C4 vs. C3	C3

## Particle Swarm Optimization

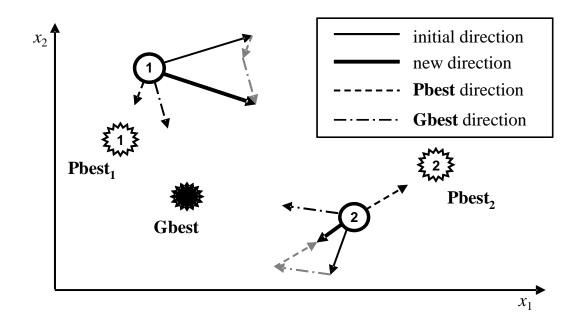
- 1995 Eberhart and Kennedy
- cooperation of swarm over the meadow
- cognitive learning: personal experience of agent
- social learning: experience of the whole swarm

## Swarm update

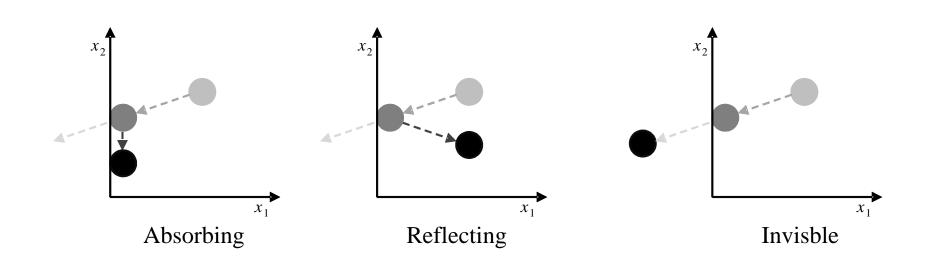
$$\mathbf{x}_{q}(i) = \mathbf{x}_{q}(i-1) + \mathbf{v}_{q}(i-1)$$

$$\mathbf{v}_{q}(i) = w \cdot \mathbf{v}_{q}(i-1) + c_{1} \cdot \mathbf{rnd}_{q} \Big[ \mathbf{Pbest}_{q}(i-1) - \mathbf{x}_{q}(i-1) \Big] \\ + c_{2} \cdot \mathbf{rnd}_{q} \Big[ \mathbf{Gbest}(i-1) - \mathbf{x}_{q}(i-1) \Big]$$

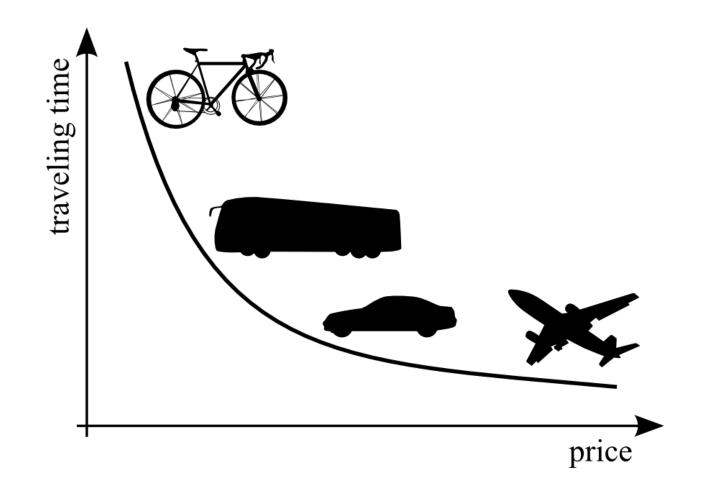
## Swarm update





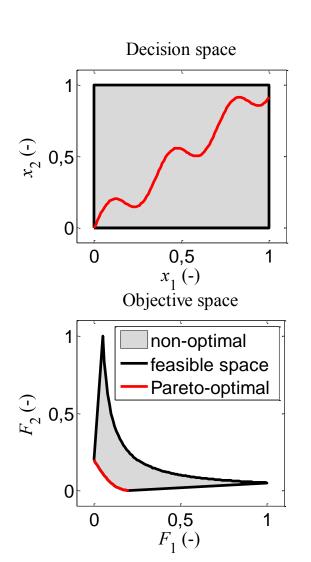


### Multi-objective optimization

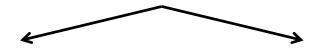


### Pareto front

- Trade-off solution
- Decision space vs.
   Objective space
- Two goals accuracy vs. Distribution
- Choice of final solution
- Pareto front shapes



#### Multi-objective strategies



Aggregating methods

Transform to SOOP Single solution

How to choose w?

**MO Optimization** 

More complex routine

Set of Pareto optimal

Extra information

**Decision making** 

$$F = \sum_{m=1}^{M} w_m F_m, \sum_{m=1}^{M} w_m = 1.$$

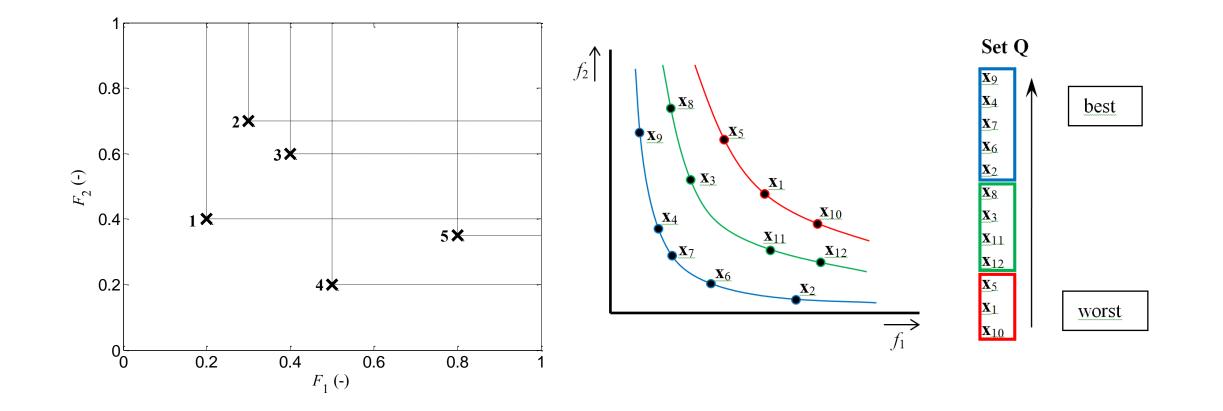
#### **Dominance concept**

Solution  $\mathbf{x}_1$  is said to dominate the other solution  $\mathbf{x}_2$ , if both conditions 1 and 2 are true:

1. Solution  $\mathbf{x}_1$  is no worse than  $\mathbf{x}_2$  in all objectives.

2. Solution  $\mathbf{x}_1$  is strictly better than  $\mathbf{x}_2$  in at least one objective.

# Dominance concept

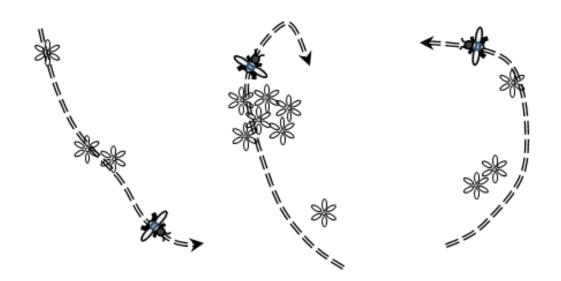




Nanbo, J., Rahmat-Samii, Y. "Advances in Particle Swarm Optimization for Antenna Designs: Real-Number, Binary, Single-Objective and Multiobjective Implementations," IEEE Transactions on Ant. Propag., vol. 55, no. 3, pp. 556-567, 2007.

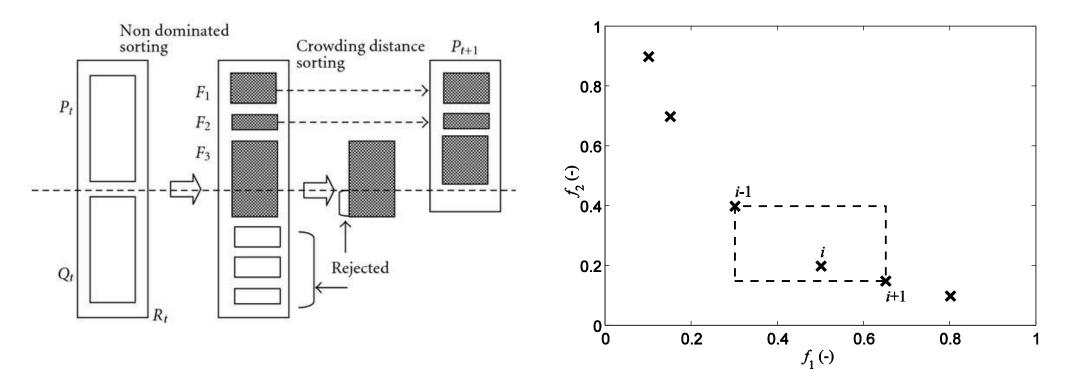
 gbest – closest solution from external archive

 pbest – first nondominated solution found by particle



#### NSGA-II

Deb, K., Pratap, A., Agarwal, S., Meyarivan, T. " A fast and elitist multiobjective genetic algorithm: NSGA-II," IEEE Transactions on Evol. Comput., vol. 6, no. 2, pp. 182-197, 2002.



- Fast Optimization ProcedureS
- http://antennatoolbox.com/fops-about.php
- single- and multi-objective codes
- chains from individual methods
- Iocal methods: steepest descent, Newton method
- global methods: Nelder Mead, GA, PSO, DE, SOMA …

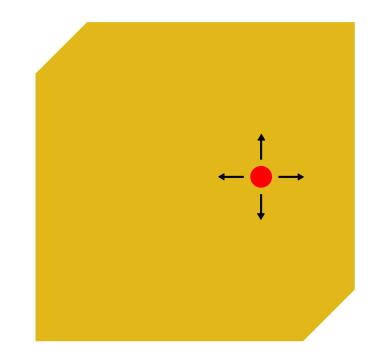
## **Feeding Point**

#### **Problem:**

Find proper point on antenna for coaxial port.

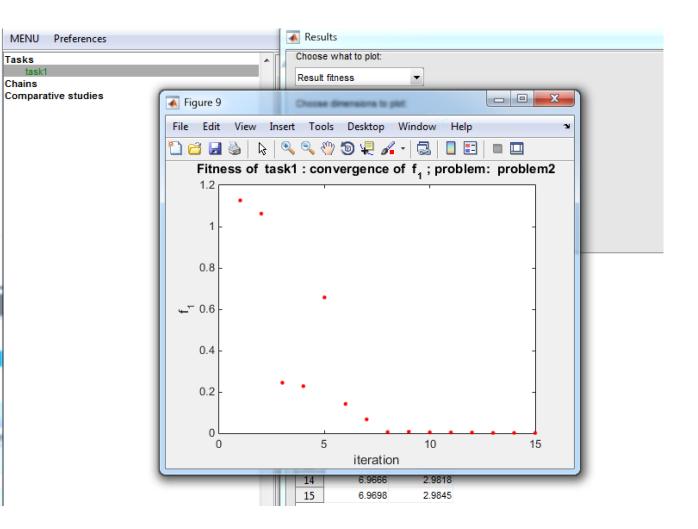
Decision space:  $\mathbf{x} = [x_1, x_2]$ 

Objective space  $f = \left( \operatorname{Re} \left\{ Z_{inp}(\mathbf{x}) \right\} - 50 \right)^2 + \left( \operatorname{Im} \left\{ Z_{inp}(\mathbf{x}) \right\} - 0 \right)^2$ 

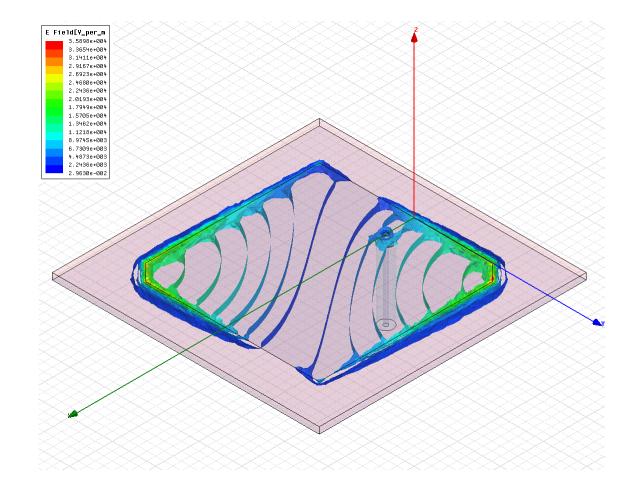


# Feeding Point

Algorithm settings
Load algorithm settings from file
Number of iterations:
30
Number of agents:
20
Inertia weight (W):
0.6 0.4
Cognitive learning factor (C1):
1.5
Social learning factor (C2):
1.5
Boundary type: reflecting
Confirm settings



# Feeding Point

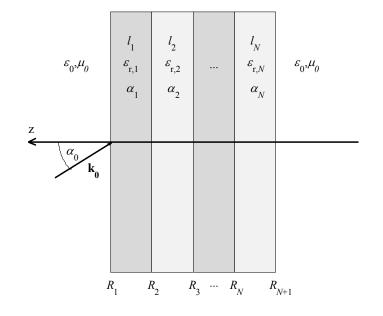


## Filter design

#### **Problem:**

Find proper material and width of layers to design band pass filter.

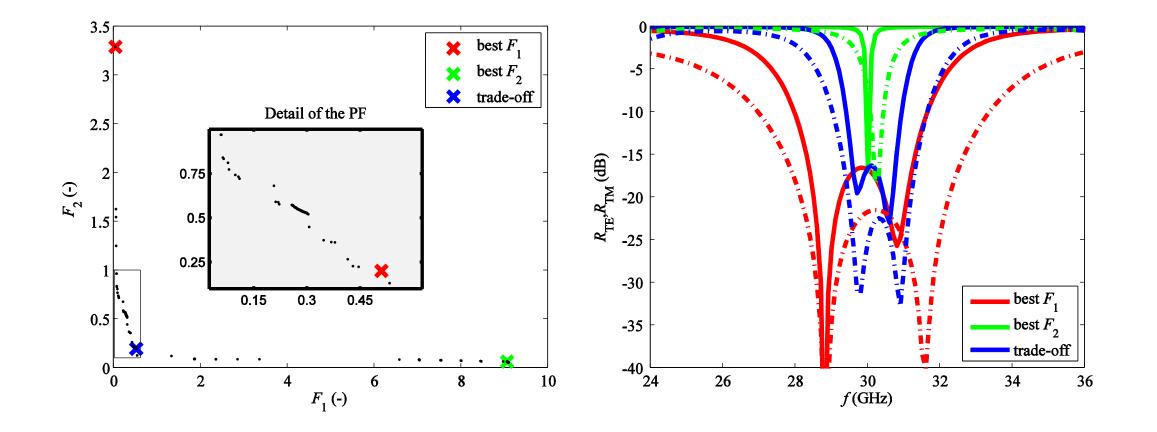
Decision space:  $\mathbf{x} = [l_{1}, \varepsilon_{1}, l_{2}, \varepsilon_{2}, ..., l_{7}, \varepsilon_{7}]$ Objective space  $F_{1} = \frac{1}{P} \sum_{p=1}^{P} \left[ \left| R_{1,\text{TE}} \left( f_{p} \right) \right|^{2} + \left| R_{1,\text{TM}} \left( f_{p} \right) \right|^{2} \right]$   $F_{2} = \frac{1}{S} \sum_{r=1}^{S} \left[ 2 - \left| R_{1,\text{TE}} \left( f_{s} \right) \right|^{2} - \left| R_{1,\text{TM}} \left( f_{s} \right) \right|^{2} \right]$ 



# Filter design

Tasks Chains	A	Add task Add chain Add comparative s	tudy
Comparative studies		Name:	
		task1	
		Algorithm:	Problem definition
		MO_NSGA-II	Problem name:
		Settings:	FilterProblem
		Change algorithm settings	Limits:
		Change algentation settings	[0.5*ones(1,7), ones(1,7)]
		Problem:	[3*ones(1,7), 10*ones(1,7)]
		user defined	Fitness function:
		Stop conditions:	@(x) {1/P*sum(rTE(fP)^2); 1/S*sum(1-rTE(fS)^2)}
		1 @(x, y)x > nlterations	Constraints function (optional):
		Add a	n
			Problem vectorized:
			Advanced problem settings
			Discrete variables (optional):
			{[0.568, 1.526,], [2.28, 3.38,],}

## Filter design



# Chain

MENU Preferences		
Tasks Chains	*	Add task Add chain Add comparative study
myChain task1 task2		Name:
Comparative studies		chain1
		Algorithm: MO_GDE3  MO_NSGA-II MO_GDE3
		<< +
		Settings: MO_GDE3 task will be modified. Change algorithm settings
		Problem: MODTLZ1
		Same stop conditions for all tasks:  Stop conditions of MO_GDE3:
		1 @(x, y)x > nlterations
		Add another stop condition

# **Comparative Study**

Name:							
Algorithm:							
	Task 1	Task 1 Task 2					
Chain 1	MO_GDE3		MO_NSGA-II	>>			
Chain 2	MO_GDE3				J		
	Add cha	in to CS	;	۱]	]		
Settings: MO_G	DE3 task will be n	nodified					
Change a	lgorithm settings						
Problem:							
MOPOL			OFON OKUR	*			
			OPOL				
	<	<		Ŧ			
Number of runs	c						
1	0						
Request:							
Spread	▼ >		enerationalDistance pread	*			
	<	<		+			

## **Comparative Study**

Tasks										
Chains	<b>(</b>	Add tasl	k Add chain	Add com	parative stu	udy				
myChain										
task1										
task2		Name:								
Comparative studies										
comparativeStudy1			C(	mparativeSt	tudy2					_
chain1	Results									X
task1		Algorith	m							
task2 chain2	Choose metric to show:									
task1	Caraad									
chain3	Spread	•								
task1										
task2			chain1, MOF	DN chain2,	MOFON	hain3, MOKUR	chain4, MOKUR	chain5, MOPOL	chain6, MOPOL	
chain4	Run1		0.09	99	0.1091	0.1749	0.2018	0.1585	0.2310	
task1	Run2		0.08	44	0.1074	0.1764	0.2193	0.3772	0.2155	
chain5 task1	Run3		0.10	24	0.1157	0.1822	0.2418	0.1873	0.2259	
task2	Run4		0.10	51	0.1077	0.1910	0.1816	0.1849	0.4289	
chain6	Run5		0.09	58	0.1228	0.2030	0.1870	0.1712	0.2003	
task1	Run6		0.12	50	0.1098	0.1720	0.2179	0.1812	0.2469	
	Run7		0.10	69	0.1163	0.1901	0.1958	0.1901	0.2525	
	Run8		0.10	26	0.1253	0.2117	0.2099	0.2038	0.4875	
	Run9		0.09	07	0.1199	0.1930	0.1886	0.1879	0.2247	
	Run10		0.09	78	0.1157	0.1948	0.1949	0.1948	0.2197	
	Mean		0.1(	10	0.1150	0.1889	0.2039	0.2037	0.2733	
	Standard deviation	on	0.01	08	0.0064	0.0127	0.0185	0.0622	0.0995	
	Minimum		0.08	44	0.1074	0.1720	0.1816	0.1585	0.2003	
	Maximum		0.12	50	0.1253	0.2117	0.2418	0.3772	0.4875	

## **Comparative Study**

Tasks										
Chains	<b>(</b>	Add tas	k Add chain	Add com	parative stu	udy				
myChain										
task1										
task2		Name:								
Comparative studies										
comparativeStudy1			C(	mparativeSt	tudy2					_
chain1	Results									X
task1		Algorith	m							
task2 chain2	Choose metric to show:									
task1	Caraad									
chain3	Spread	•								
task1										
task2			chain1, MOF	DN chain2,	MOFON	hain3, MOKUR	chain4, MOKUR	chain5, MOPOL	chain6, MOPOL	
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Thank you for your attention!



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VYSOKÉ UČENÍ FAKULTA ELEKTROTECHNIKY TECHNICKÉ A KOMUNIKAČNÍCH V BRNĚ TECHNOLOGIÍ





