Instituto Politécnico Nacional

Computer Science Department

CINVESTAV-IPN

MOEA APPLIED ON ELECTRIC CIRCUITS

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INTRODUCTION

- A wide variety of real world problems have several (often conflicting) objectives that need to be optimized at the same time.
- They are called multi-objective optimization problems (MOPs) and their solution involves finding a set of decision variables that represent the best trade-offs among all the objectives.

DEFINITION OF A MOP

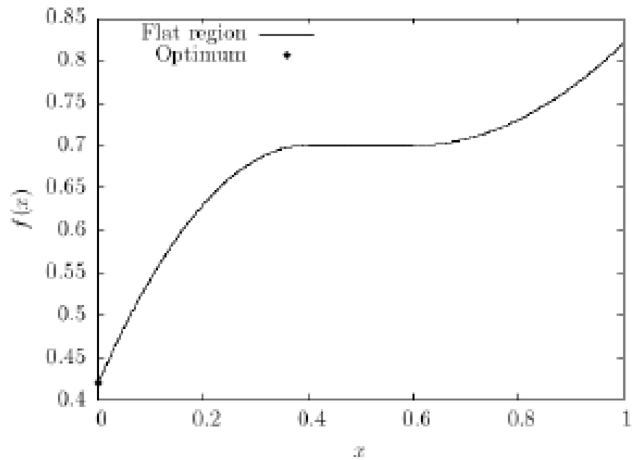
$$\text{Minimize} \quad \vec{F}(\vec{x}) := (f_1(\vec{x}), f_2(\vec{x}), \ldots, f_m(\vec{x})) \tag{1}$$

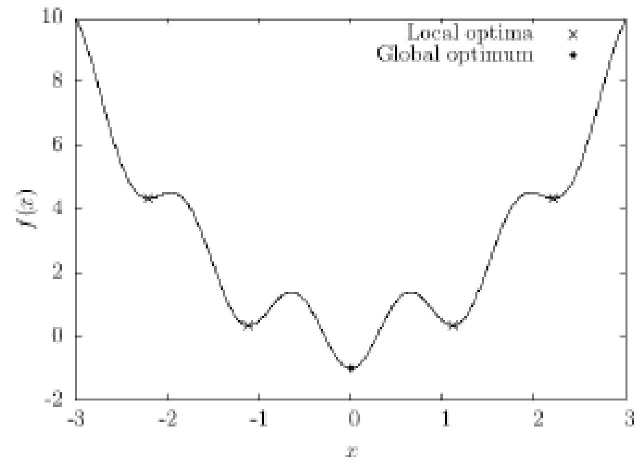
$$\text{subject to} \quad g_i(\vec{x}) \geq 0 \quad i = \{1, 2, \ldots, p\} \tag{2}$$

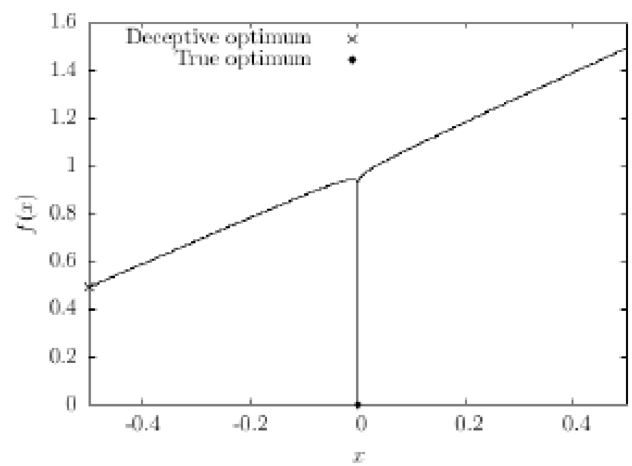
$$h_i(\vec{x}) = 0 \quad i = \{1, 2, \ldots, q\}, \tag{3}$$

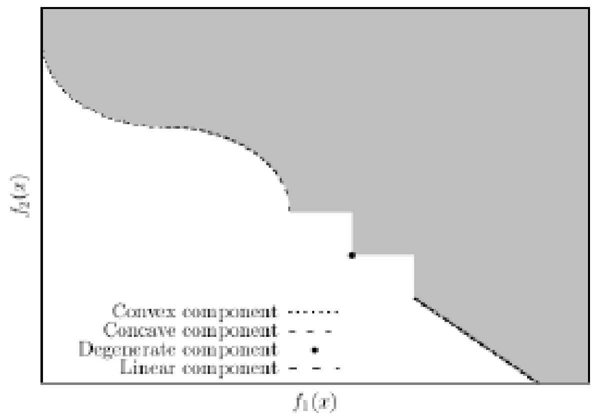
where $\vec{x}$ is the *decision variable vector* and $\vec{F}$ is the vector of m (≥ 2) *objective functions* $(f_i : \mathbb{R}^n \to \mathbb{R})$.

DIFFICULTIES IN MOPs

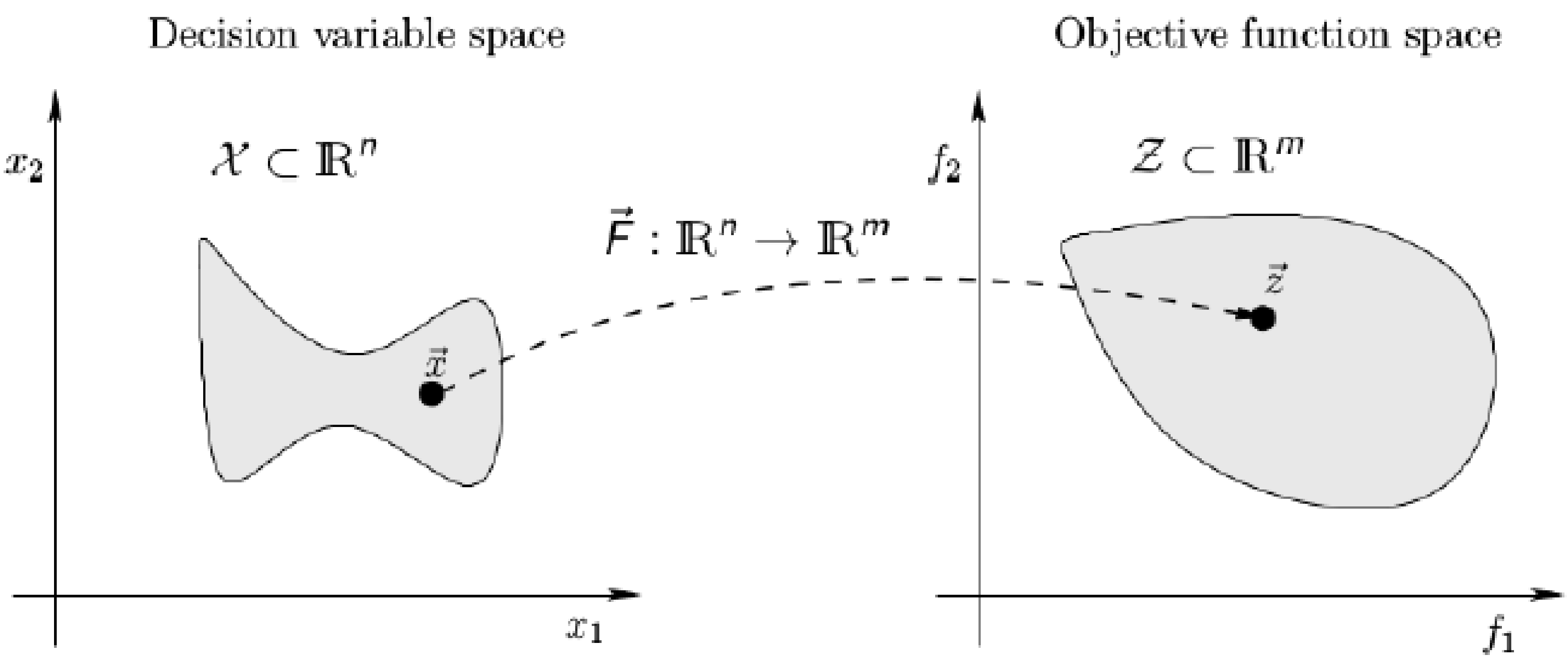








EXAMPLE OF A MOP

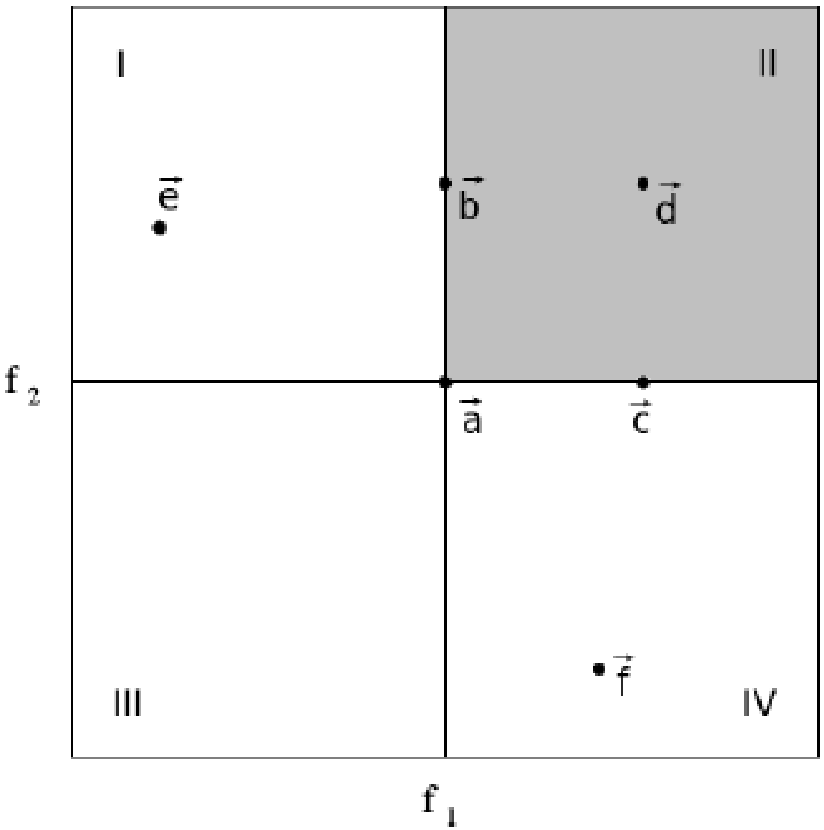


A solution $\vec{x} \in \mathcal{X}$ *dominates* a solution $\vec{y} \in \mathcal{X}$ ($\vec{x} \prec \vec{y}$), iff:

1. $\forall i \in \{1, \ldots, m\}\ f_i(\vec{x}) \leq f_i(\vec{y})$
2. $\exists j \in \{1, \ldots, m\}\ f_j(\vec{x}) < f_j(\vec{y})$

Set of *non-dominated solutions*:

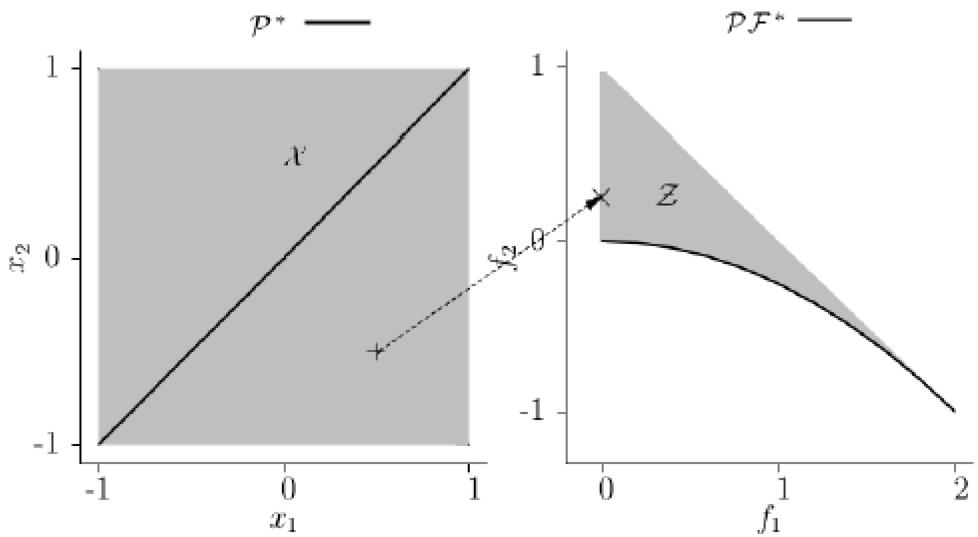
$$\{\vec{x} \in Q \subset \mathcal{X} \mid \nexists \vec{y} \in Q : \vec{y} \prec \vec{x}\}.$$



PARETO DOMINANCE

$$\textit{Pareto Optimal Set } \mathcal{P}^* := \{\vec{x} \in \mathcal{X} \mid \nexists \vec{y} \in \mathcal{X} : \vec{y} \prec \vec{x}\}$$

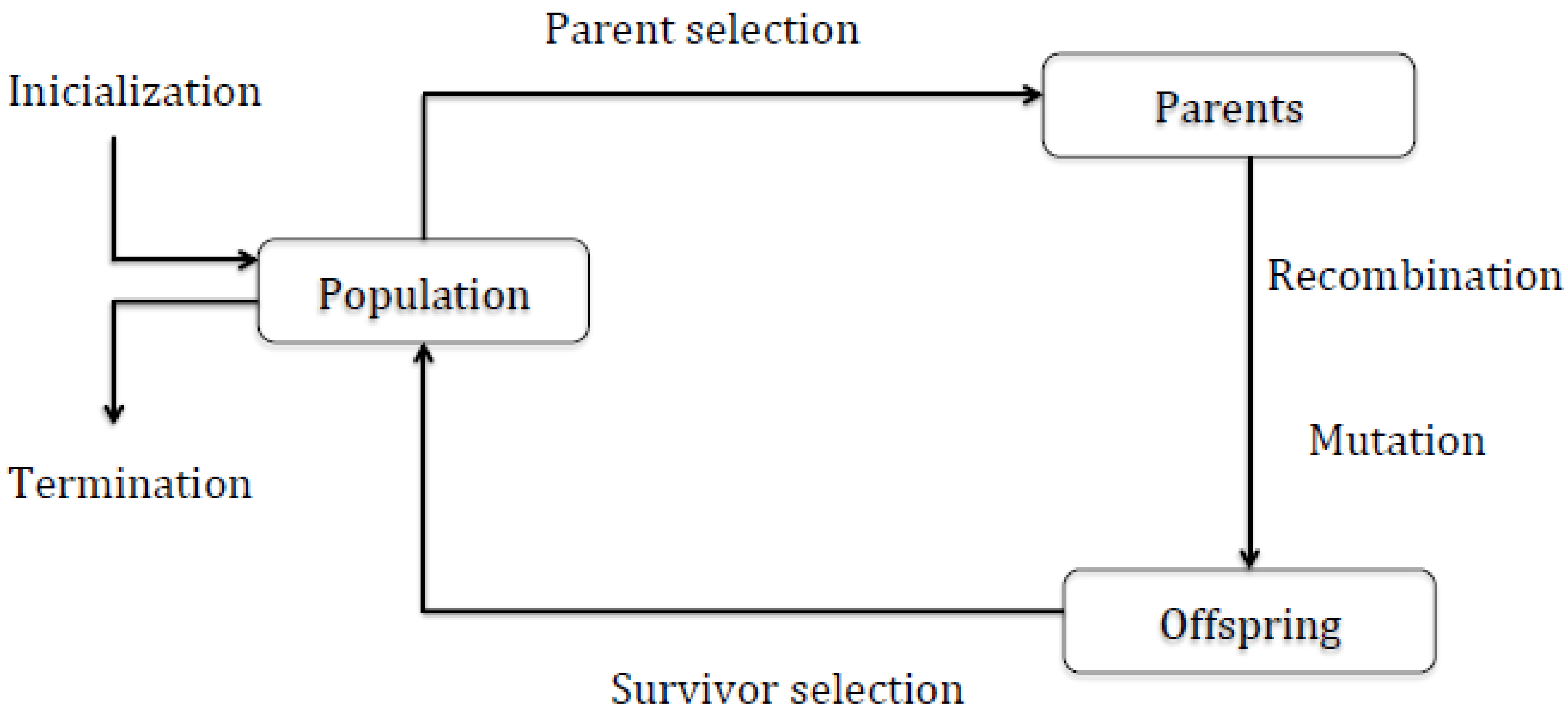
$$\textit{Pareto Optimal Front } \mathcal{PF}^* := \{\vec{F}(\vec{x}) \in \mathbb{R}^m \mid \vec{x} \in \mathcal{P}^*\}$$



$(x_1, x_2) \in \{-1, \ldots, 1\} \times \{-1, \ldots, 1\}$ $\quad$ $f_1(x_1, x_2) = |x_1 + x_2|$

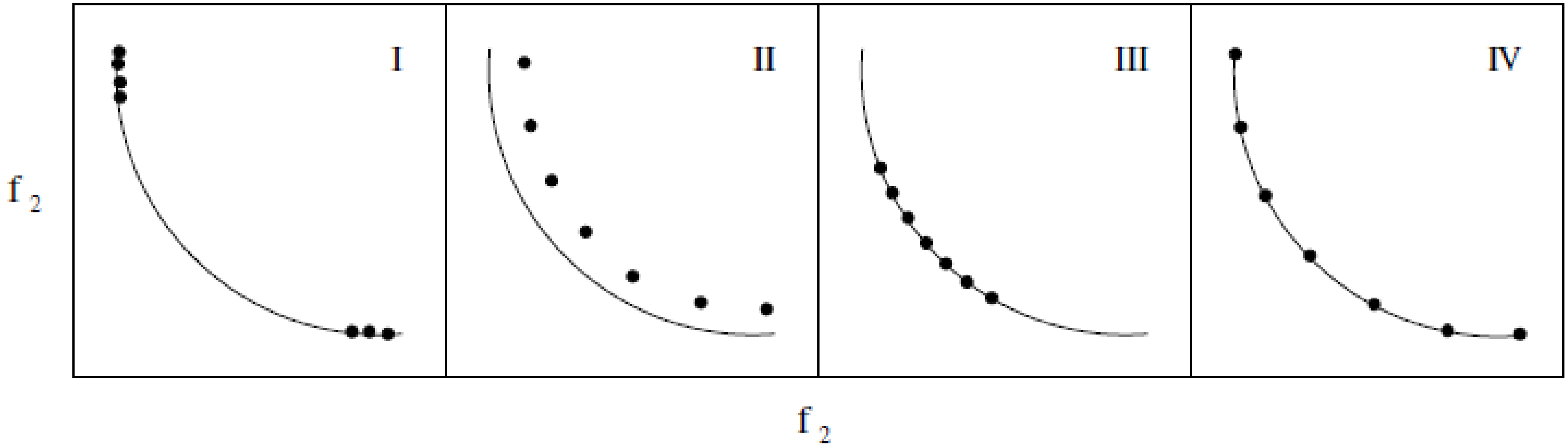
$\mathcal{P}^* = \{(x_1, x_2) \mid x_1 = x_2\}$ $\quad$ $f_2(x_1, x_2) = -x_1 x_2$

PARETO FRONT



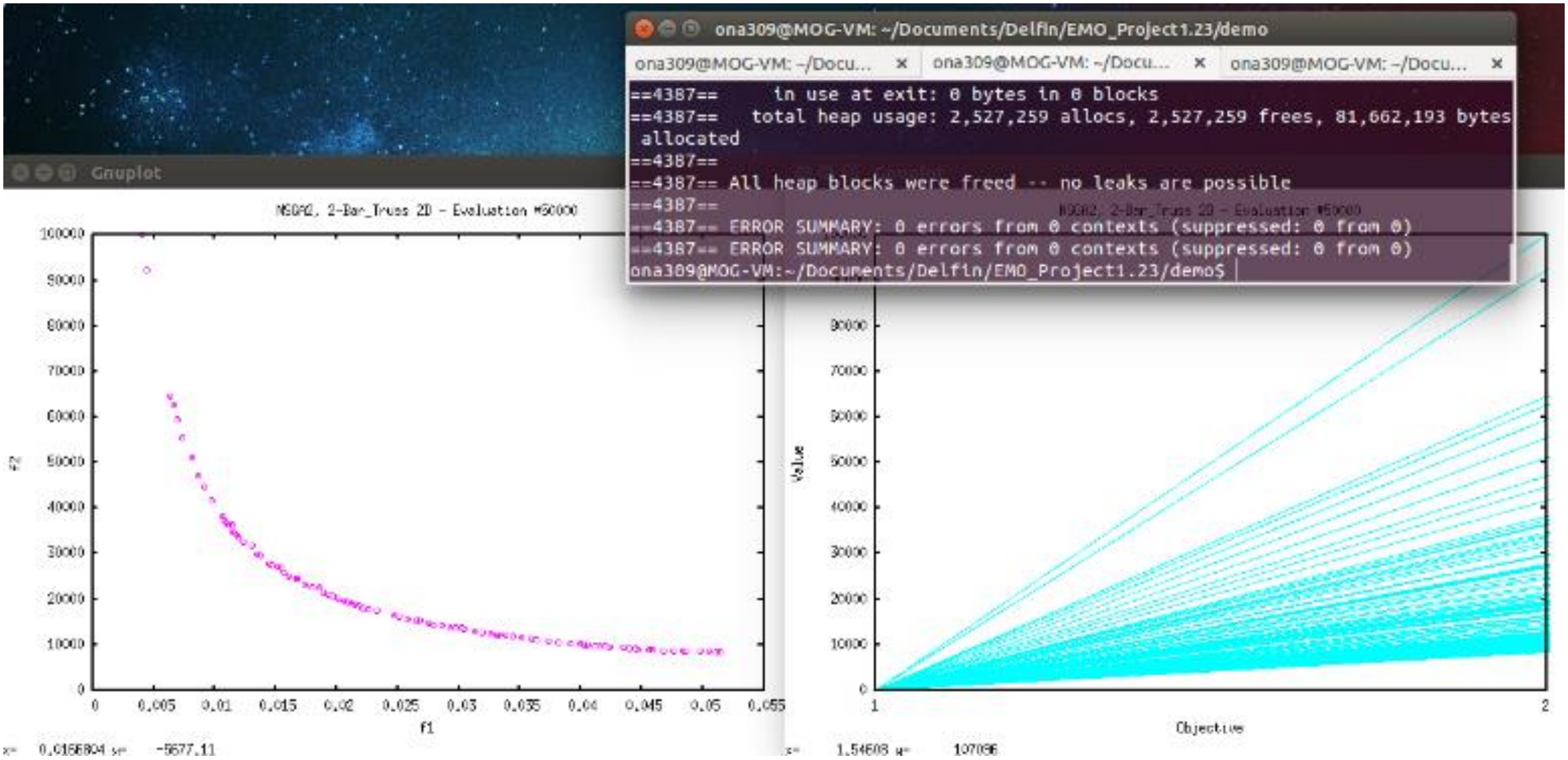
EVOLUTIONARY ALGORITHMS

- $I : \mathbb{R}^m \to \mathbb{R}$
- Quality indicators evaluate the desired features of MOEAs:



QUALITY INDICATORS

FIRST APPROACH



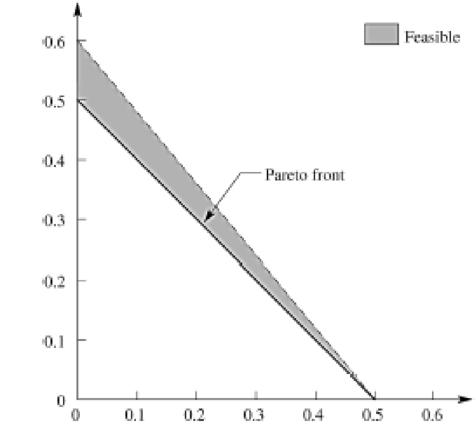


Fig. 1. Two-objective version of the C1-DTLZ1 problem.

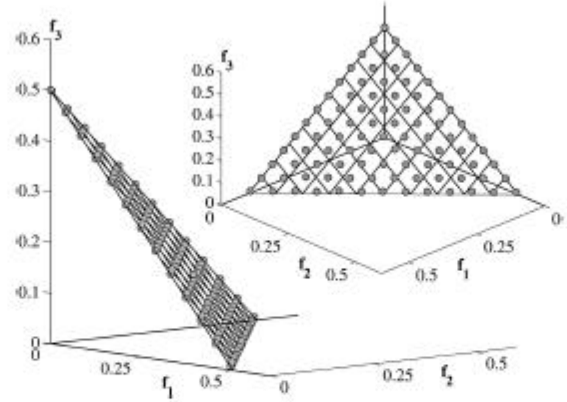


Fig. 3. Obtained solutions using NSGA-III on the three-objective C1-DTLZ1 problem.

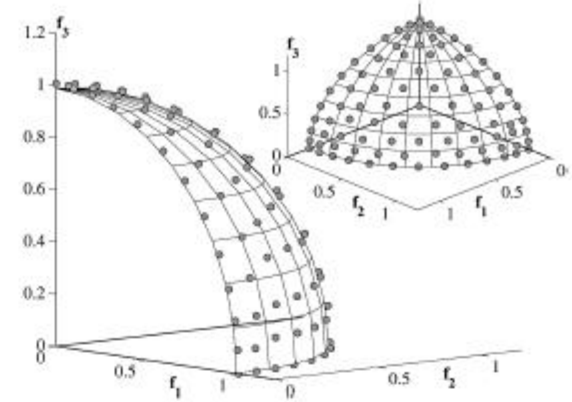


Fig. 5. Obtained solutions using NSGA-III on the three-objective constrained C1-DTLZ3 problem.

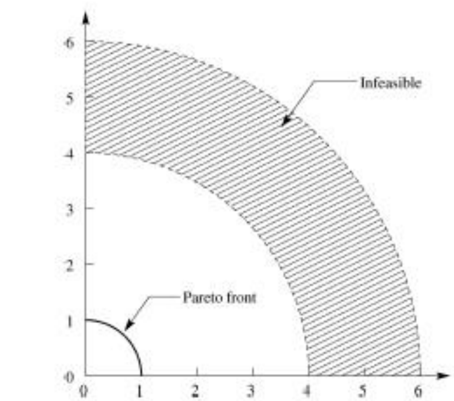


Fig. 2. Two-objective version of the C1-DTLZ3 problem.

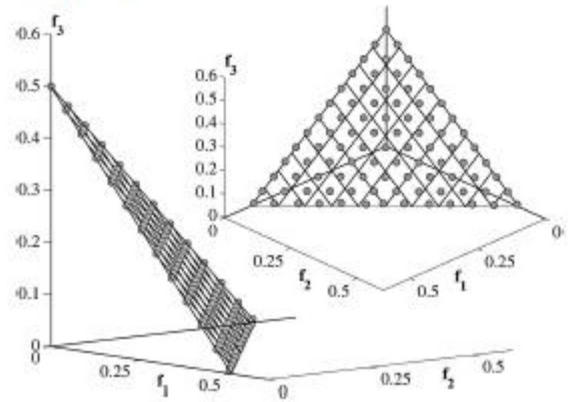


Fig. 4. Obtained solutions using C-MOEA/D approach on the three-objective C1-DTLZ1 problem.

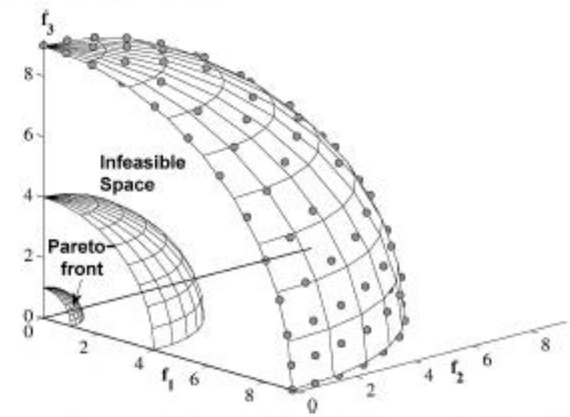
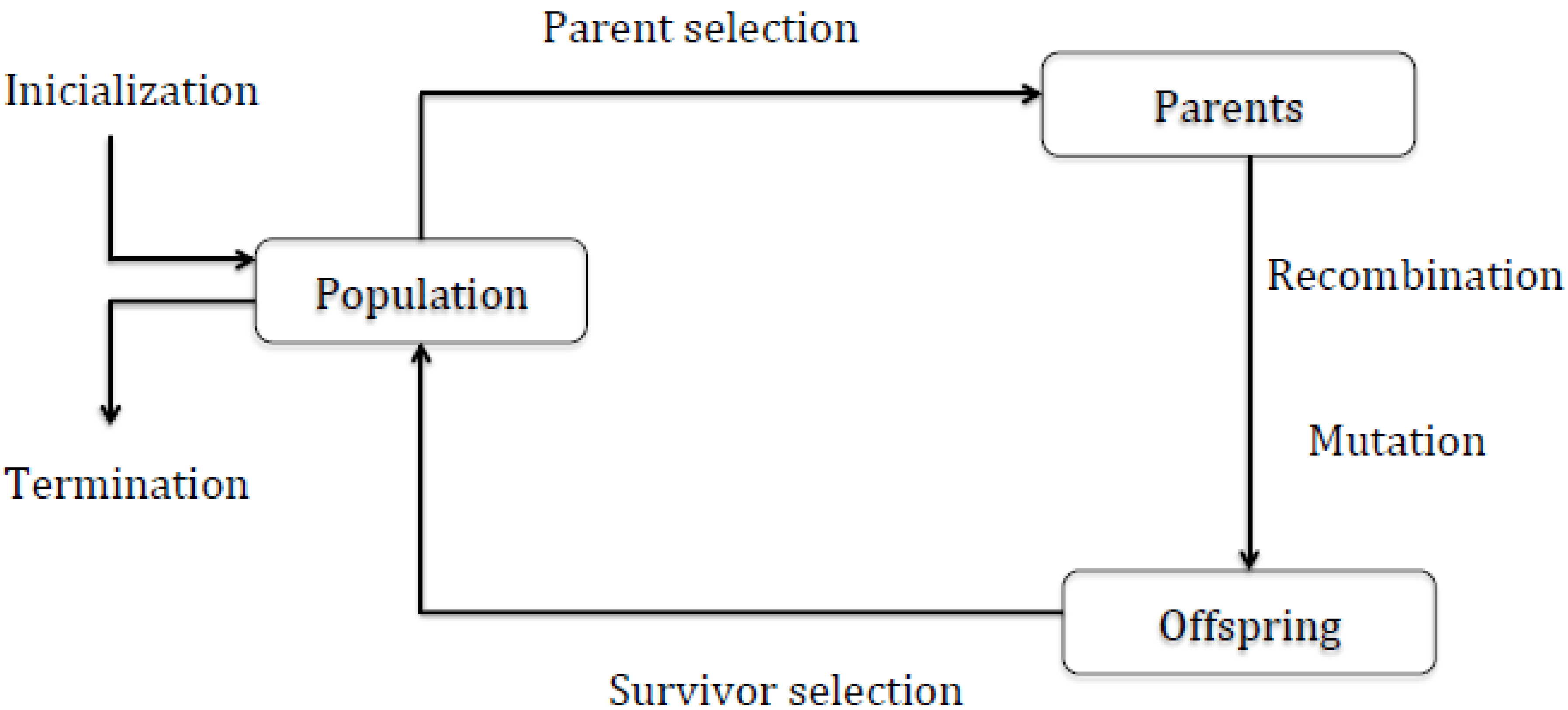


Fig. 6. Obtained solutions using the C-MOEA/D on the three-objective constrained C1-DTLZ3 problem.

NSGA-3 WITH RESTRICTIONS

NON-DOMINATED SORTING GENETIC ALGORITHM

EA ON NSGA-3



Parent selection
Inicialization
Parents
Population
Recombination
Mutation
Termination
Offspring
Survivor selection

CONSTRAINT DOMINATION

A solution x(1) dominates x(2):

1. If x(1) is feasible and x(2) is infeasible:
2. If x(1) and x(2) are infeasible and x(1) has a smaller constraint violation value CV(x).
3. If x(1) and x(2) are feasible and x(1) dominates x(2) with the usual domination principle.

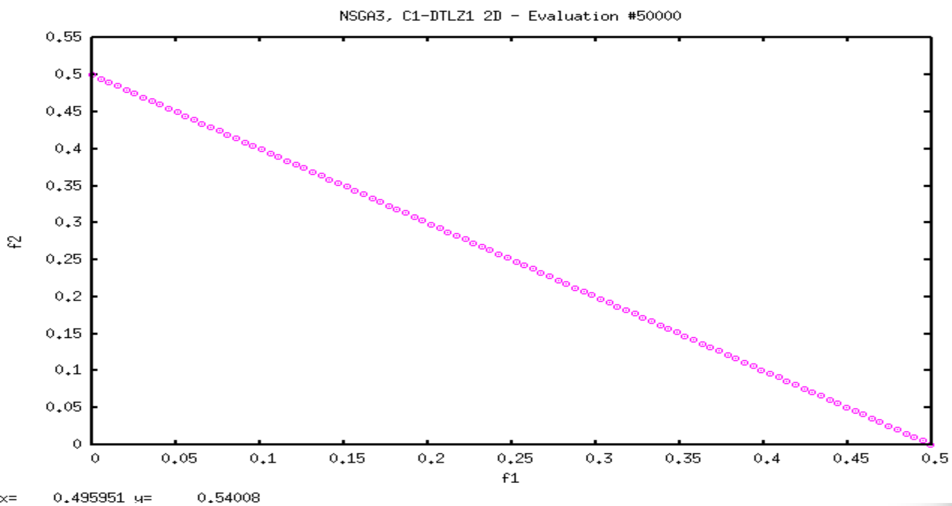
$$CV(\mathbf{x}) = \sum_{j=1}^{J} \langle \bar{g}_j(\mathbf{x}) \rangle + \sum_{k=1}^{K} |\bar{h}_k(\mathbf{x})|$$

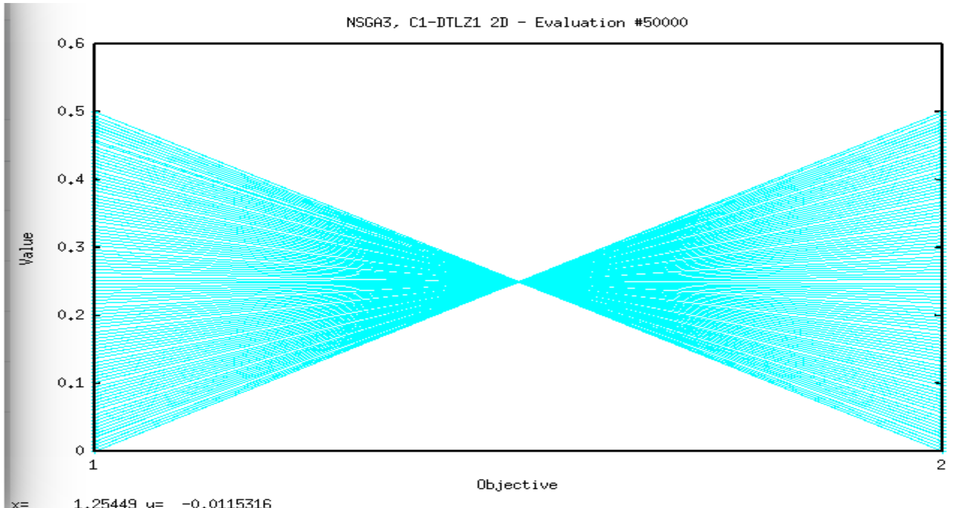
MODIFIED TOURNAMENT FOR SELECTION OF PARENTS

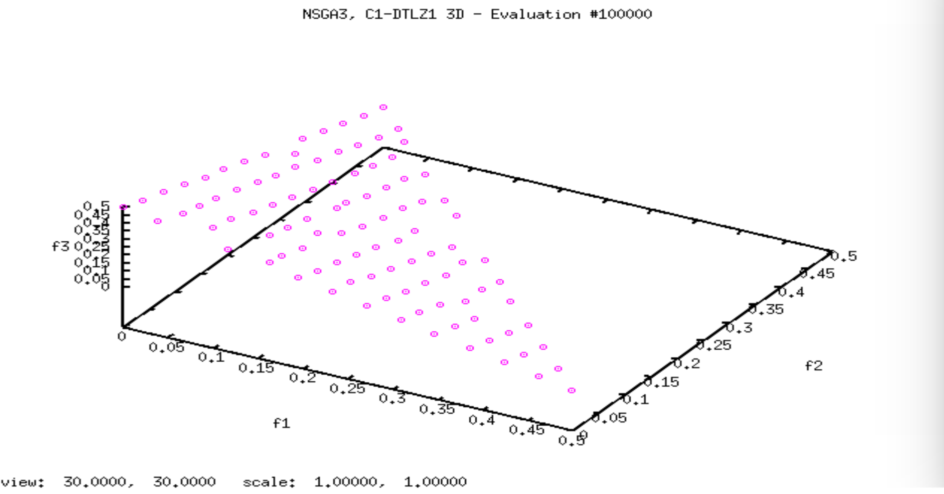
Between solution p1 and p2:

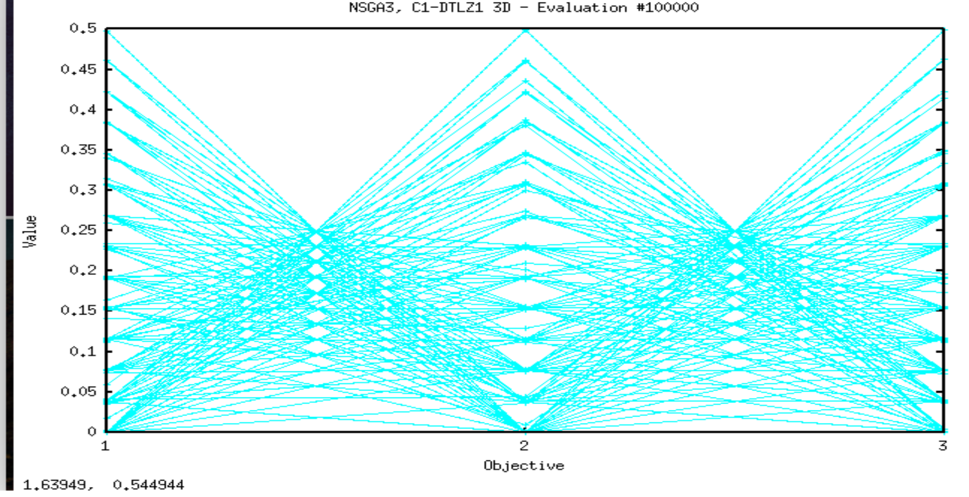
1. If one of them is feasible and the other is infeasible, select the feasible one.
2. If both p1 and p2 are infeasible, select the one with the smaller constraint violation CV.
3. If both p1 and p2 are feasible, select one at random.

RESULTS

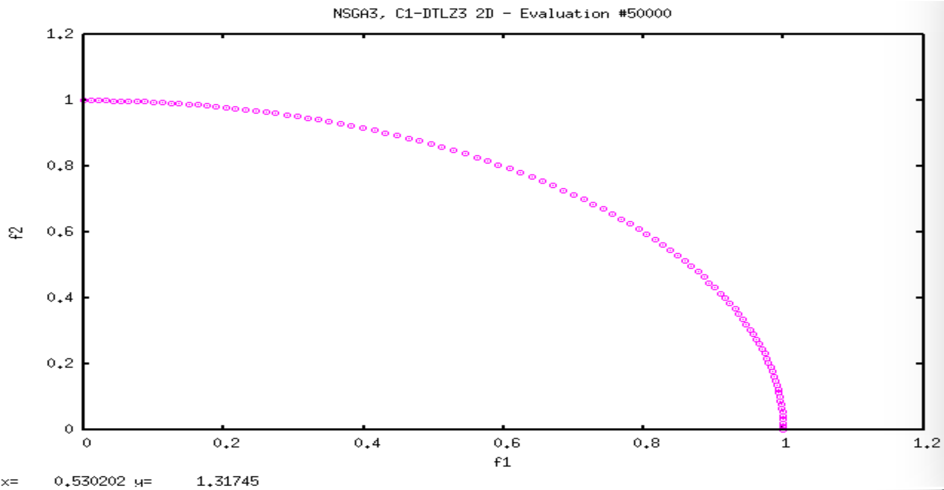

NSGA3, C1-DTLZ1 2D - Evaluation #50000
f1
f2
x= 0.495951 y= 0.54008

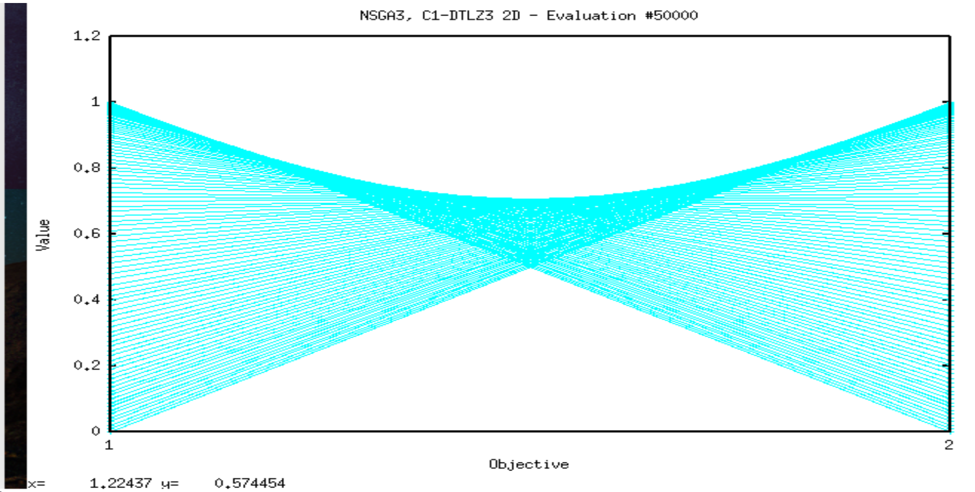

NSGA3, C1-DTLZ1 2D - Evaluation #50000
Value
Objective
x= 1.25449 y= -0.0115316

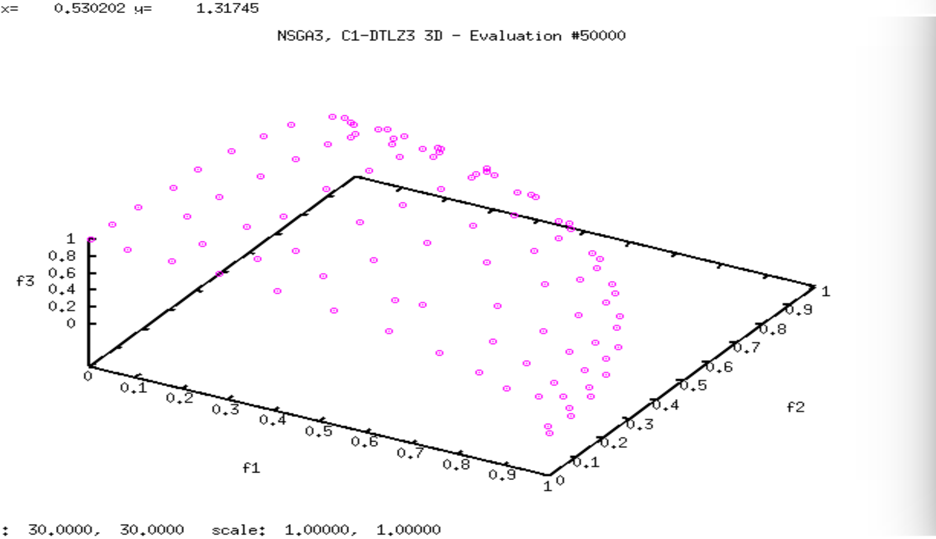

NSGA3, C1-DTLZ1 3D - Evaluation #100000
f1
f2
f3
view: 30.0000, 30.0000 scale: 1.00000, 1.00000

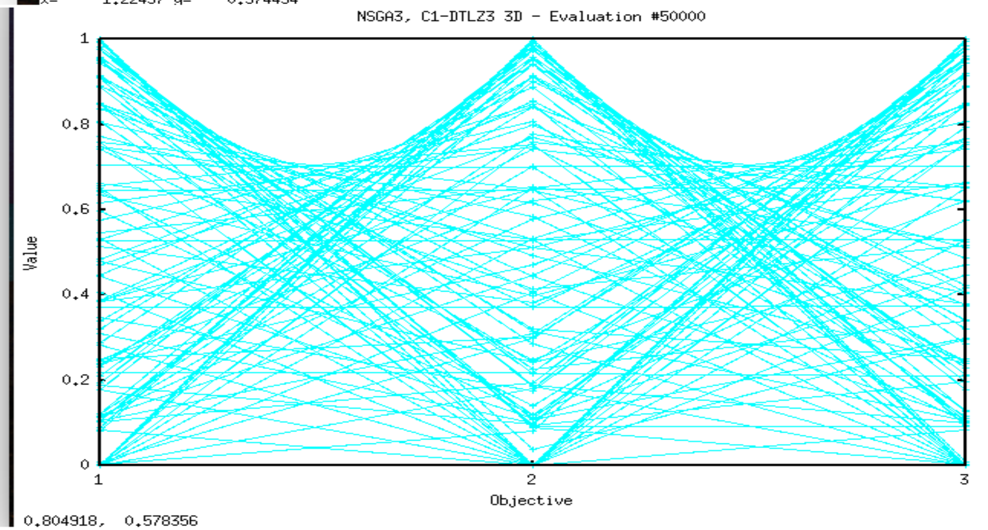

NSGA3, C1-DTLZ1 3D - Evaluation #100000
Value
Objective
1.63949, 0.544944

RESULTS

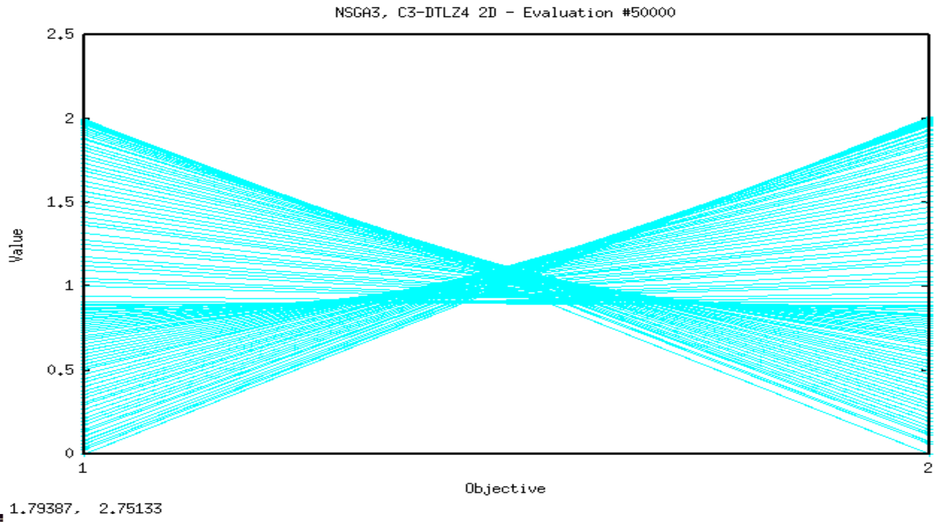

NSGA3, C1-DTLZ3 2D - Evaluation #50000
f2
f1
x= 0.530202 y= 1.31745

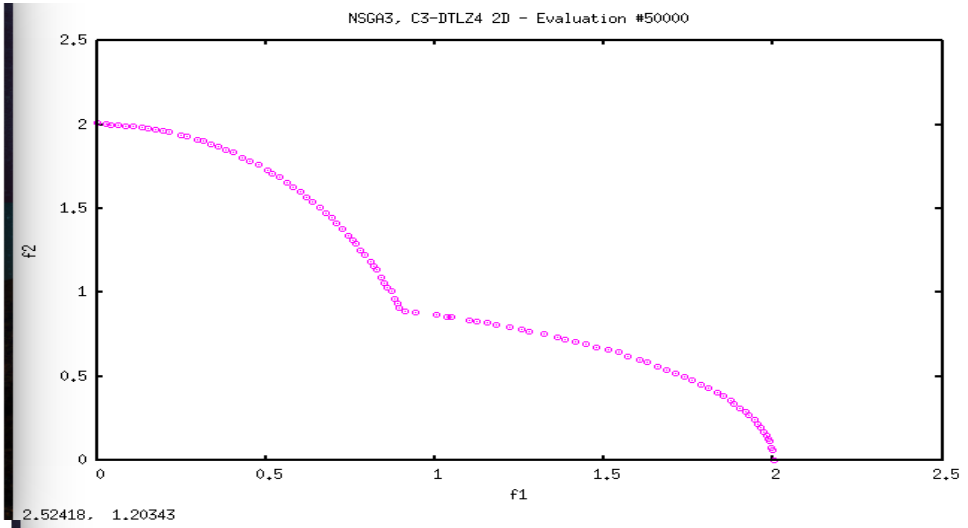

NSGA3, C1-DTLZ3 2D - Evaluation #50000
Value
Objective
x= 1.22437 y= 0.574454

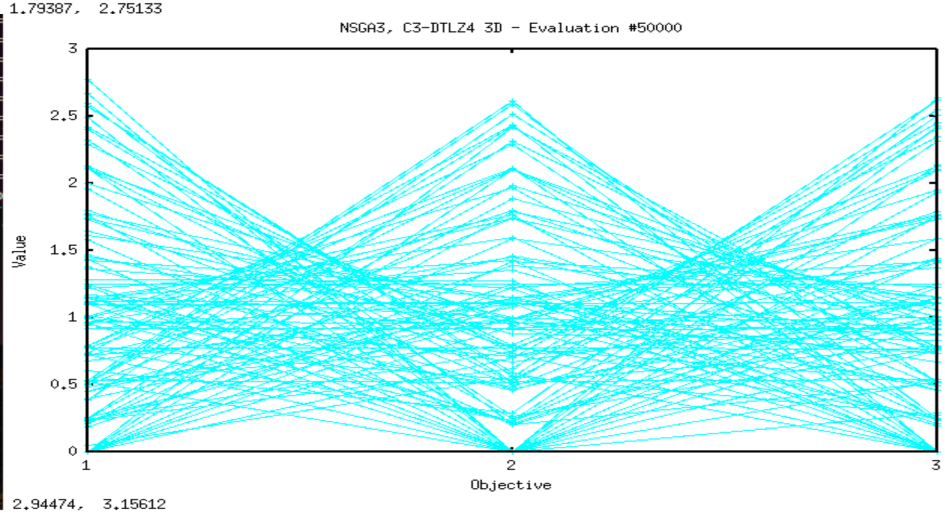

NSGA3, C1-DTLZ3 3D - Evaluation #50000
f3
f1
f2
: 30.0000, 30.0000 scale: 1.00000, 1.00000

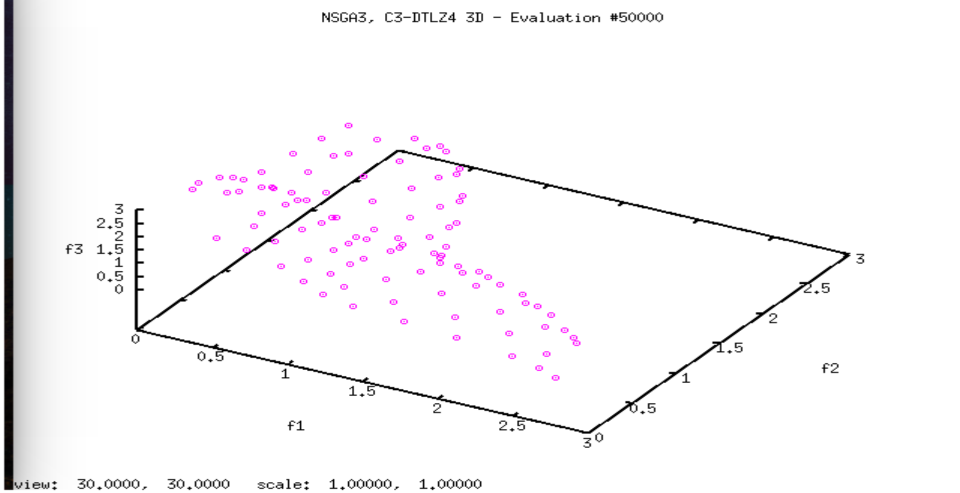

NSGA3, C1-DTLZ3 3D - Evaluation #50000
Value
Objective
0.804918, 0.578356

RESULTS


NSGA3, C3-DTLZ4 2D - Evaluation #50000
Value
Objective
1.79387, 2.75133


NSGA3, C3-DTLZ4 2D - Evaluation #50000
f2
f1
2.52418, 1.20343


NSGA3, C3-DTLZ4 3D - Evaluation #50000
Value
Objective
2.94474, 3.15612


NSGA3, C3-DTLZ4 3D - Evaluation #50000
f3
f1
f2
view: 30.0000, 30.0000 scale: 1.00000, 1.00000

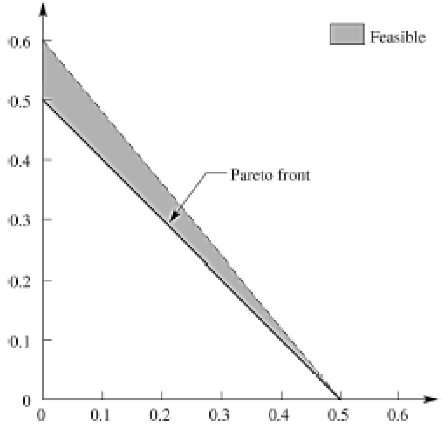


Fig. 1. Two-objective version of the C1-DTLZ1 problem.

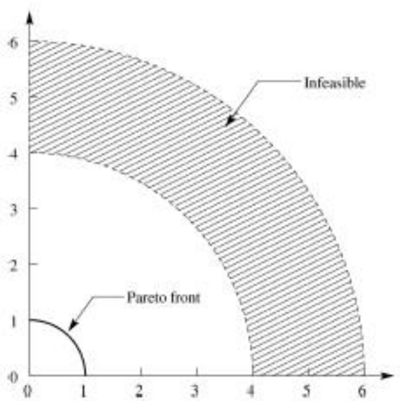


Fig. 2. Two-objective version of the C1-DTLZ3 problem.

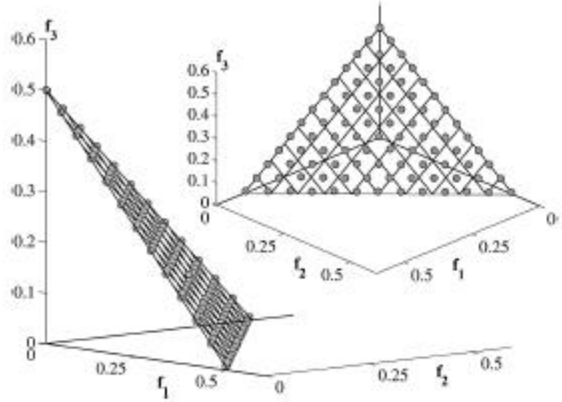


Fig. 3. Obtained solutions using NSGA-III on the three-objective C1-DTLZ1 problem.

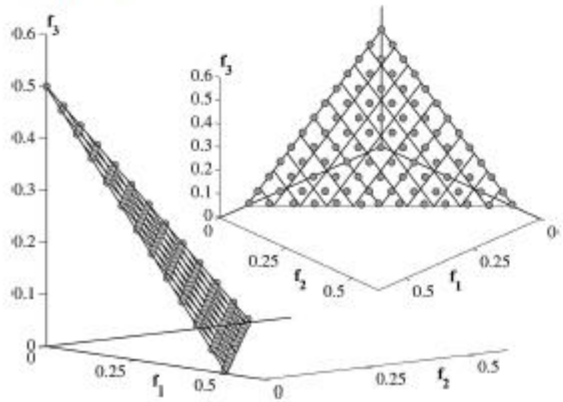


Fig. 4. Obtained solutions using C-MOEA/D approach on the three-objective C1-DTLZ1 problem.

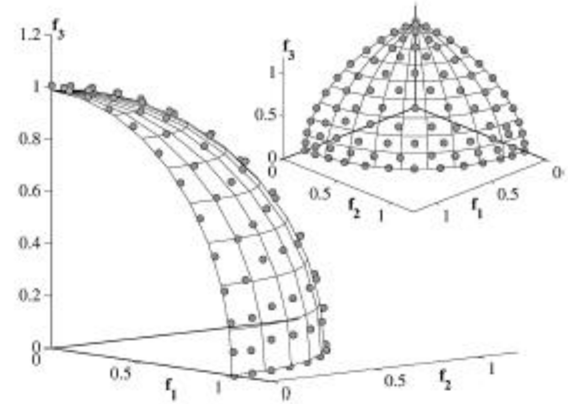


Fig. 5. Obtained solutions using NSGA-III on the three-objective constrained C1-DTLZ3 problem.

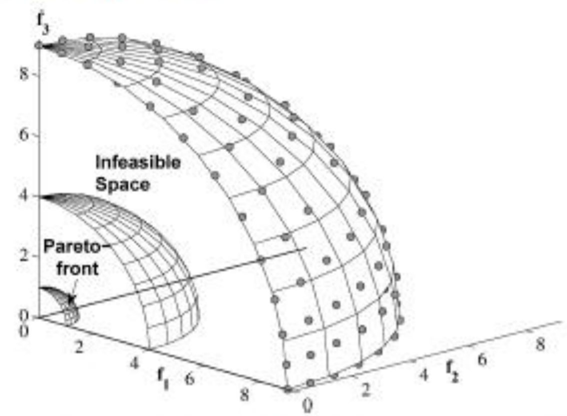
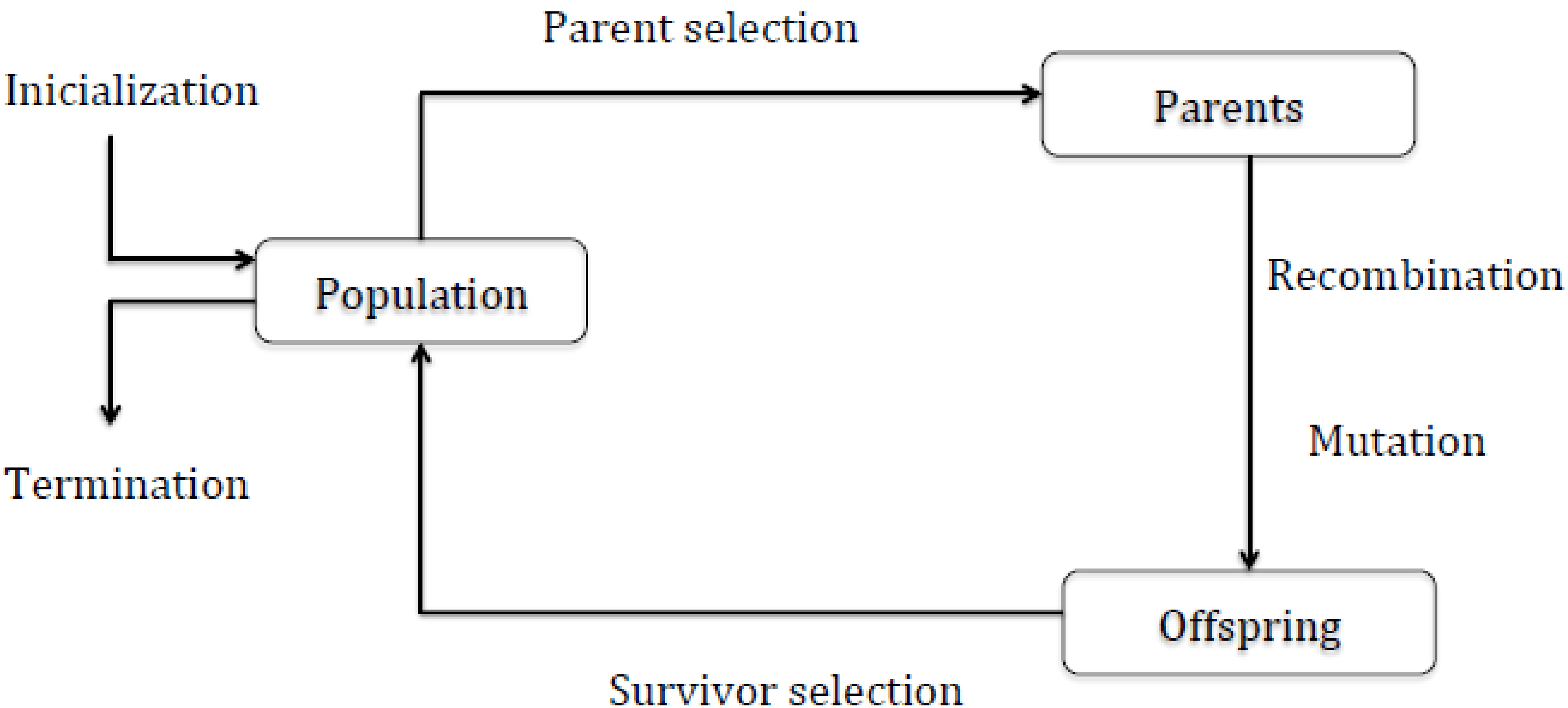


Fig. 6. Obtained solutions using the C-MOEA/D on the three-objective constrained C1-DTLZ3 problem.

MOEAD WITH RESTRICTIONS

UTILITY FUNCTIONS FOR SURVIVOR SELECTION

EA ON MOEAD



Parent selection
Inicialization
Parents
Population
Recombination
Mutation
Termination
Offspring
Survivor selection

CV AND TAU VALUES

- Violation constraint value,

  (similar to NSGA-3).

- Tau value is introduced as a threshold based on the minimum and maximum violation constraint value of the total population.

$$\tau = CV_{min} + 0.3 \ * (CV_{max} \ - \ CV_{min})$$

PARAMETERS S1 AND S2

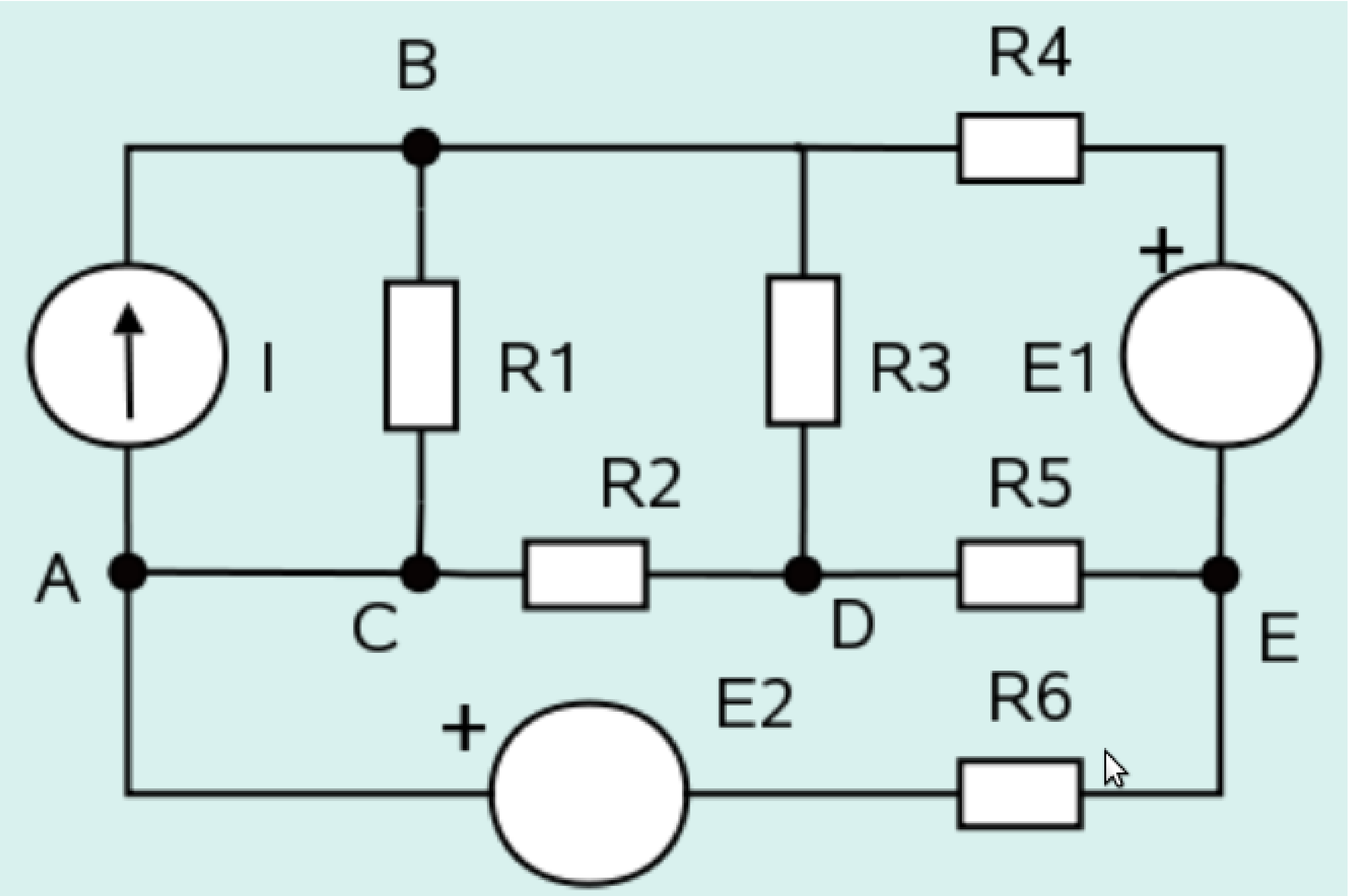
- The parameters s1 = 0.01 and s2 = 20 are coefficients to modify utility functions.

$$if\,(CV_i < \tau)$$

$$V_i^* = V_i + s1 * CV_i^2$$

$$else$$

$$V_i^* = V_i + s1 * \tau^2 + s2\,(CV_i - \tau)$$



REAL LIFE PROBLEM

INTERACTION WITH ELECTRIC CIRCUIT SIMULATOR

OBJECTIVES

There are six objectives in the circuit problem:

Maximize:

- f(1) - Open Loop Gain,
- f(2) - Unitary Gain Frequency,
- f(3) - Common Mode Rejection Rate,
- f(4) - Slew Rate,

Minimize:

- f(5) - Input Current,
- f(6) - Area.

RESULTS

	Experiment 1			
	MOEAD	MOMBI2	NSGA2	NSGA3
Run 1	5.39E+021	3.18E+025	6.65E+025	1.97E+024
Run 2	5.62E+021	4.61E+025	6.95E+025	3.81E+024
Run 3	5.57E+021	2.93E+025	7.23E+025	4.26E+024
Average	**5.53E+021**	**3.58E+025**	**6.95E+025**	**3.35E+024**

	Experiment 2			
	MOEAD	MOMBI2	NSGA2	NSGA3
Run 1	1.38E+025	3.34E+025	6.75E+025	4.36E+024
Run 2	1.30E+025	3.94E+025	6.98E+025	3.72E+024
Run 3	1.10E+025	4.77E+025	7.08E+025	4.68E+024
Average	**1.26E+025**	**4.02E+025**	**6.94E+025**	**4.25E+024**

SUMMARY

- Two algorithms (MOEAD and NSGA-3) were adapted to handle constraints and were incorporated on the EMOProject framework.
- More than 15 problems handling constrains were programed and incorporated on the EMOProject framework.
- Changes on the algorithms were tested, measured and validated on this problems.
- New algorithms were tested on a real problem and compared to existing algorithms.

CONCLUSIONS

- Evolutionary algorithms are a good approach for solving problems with a large number of variables and/or objectives that can't be explored in an exhaustive way due to complexity and/or time restrictions.
- Real problems can be adapted to be solved by evolutionary algorithms in an efficient way.

CONCLUSIONS

- Even though the physical resources (virtual machine in laptop) used for this purpose were limited, the result was obtained in a considerable time. This can be avoided using a dedicated computer.
- The results can be improved by fully adapting the original algorithms (changing mutation and crossing methods), however the delivered program is stable.