

A0M33EOA
Multi-objective Evolutionary Algorithms

Petr Pošík

Czech Technical University in Prague
Faculty of Electrical Engineering
Department of Cybernetics

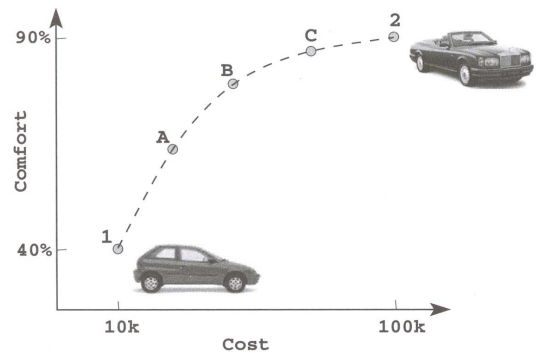
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Multi-objective Optimization

Many real-world problems involve multiple objectives.

- **Conflicting objectives**
 - A solution that is extreme with respect to one objective requires a compromise in other objectives.
 - A sacrifice in one objective is related to the gain in other objective(s).
- **Illustrative example: Buying a car**
 - two extreme hypothetical cars 1 and 2,
 - cars with a trade-off between cost and comfort – A, B, and C.



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Which solution out of all of the trade-off solutions is the best with respect to all objectives?

- Without any further information those trade-offs are indistinguishable.
- **A number of optimal solutions is sought in multiobjective optimization!**

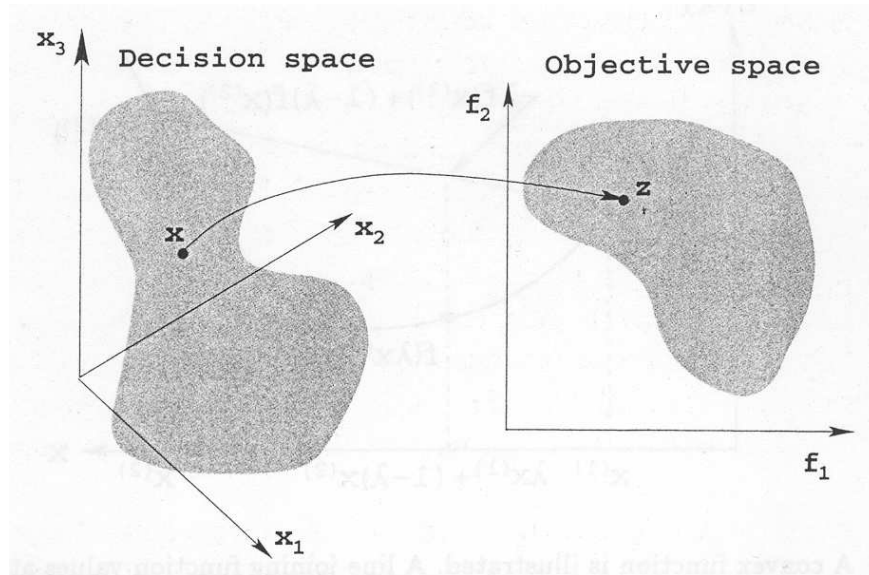
Multi-Objective Optimization: Definition

General form of multi-objective optimization problem

$$\begin{array}{ll}
 \text{Minimize/maximize} & f_m(x), \quad m = 1, 2, \dots, M; \\
 \text{subject to} & g_j(x) \geq 0, \quad j = 1, 2, \dots, J; \\
 & h_k(x) = 0, \quad k = 1, 2, \dots, K; \\
 & x_i^{(L)} \leq x_i \leq x_i^{(U)}, \quad i = 1, 2, \dots, n.
 \end{array}$$

- x is a vector of n decision variables: $x = (x_1, x_2, \dots, x_n)$.
- **Decision space** is constituted by variable bounds that restrict the value of each variable x_i to take a value within a lower $x_i^{(L)}$ and an upper $x_i^{(U)}$ bound.
- Inequality and equality constraints g_j and h_k .
- A solution x that satisfies all constraints and variable bounds is a **feasible solution**, otherwise it is called an **infeasible solution**.
- **Feasible space** is a set of all feasible solutions.
- Objective functions $f(x) = (f_1(x), f_2(x), \dots, f_M(x))$ constitute a multi-dimensional **objective space**.

Decision and Objective Space



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- For each solution x in the decision space, there exists a point in the objective space

$$f(x) = z = (z_1, z_2, \dots, z_M)^T$$

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Motivation Example: Cantilever Design Problem

Task: design a beam, defined by two *decision variables*,

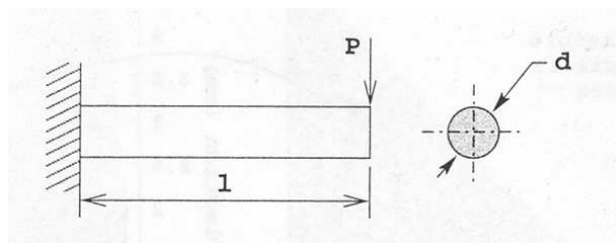
- diameter d and
- length l ,

that can carry an end load P and is optimal with respect to *objectives*

- f_1 : cantilever weight (to be minimized),
- f_2 : endpoint deflection (to be minimized),

subject to the *constraints* that

- the developed maximum stress σ_{max} is less than the allowable stress S ,
- the end deflection δ is smaller than a specified limit δ_{max} .

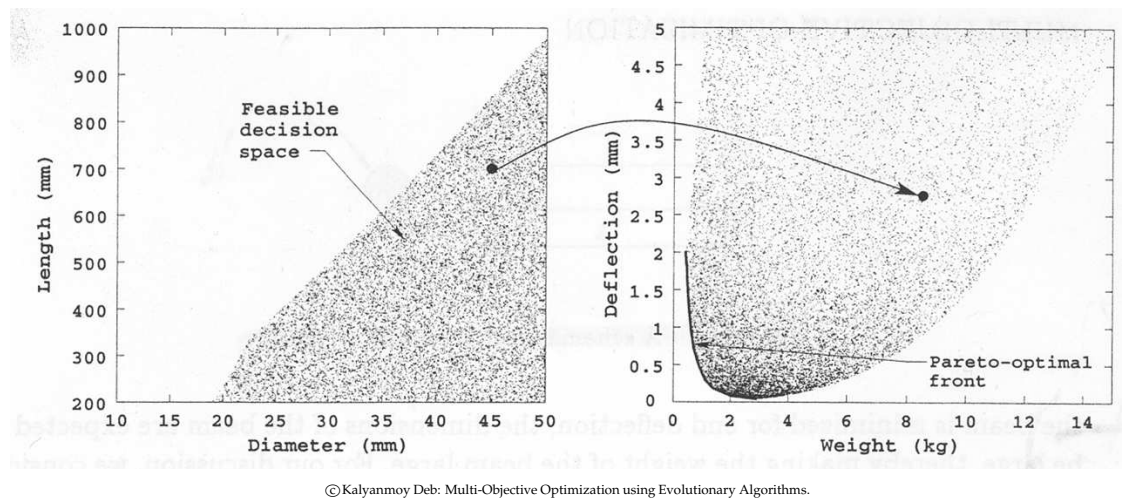


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Cantilever Design Problem: Decision and Objective Space



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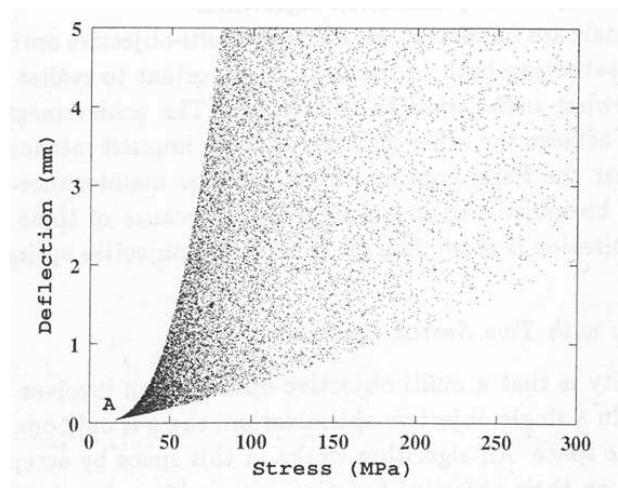
Non-Conflicting Objectives

Existence of multiple trade-off solutions:

- Only if the objectives are in conflict with each other.
- If this does not hold then the cardinality of the Pareto-optimal set is one. (The optimum solutions w.r.t. individual objectives are the same.)

Example: Cantilever beam design problem:

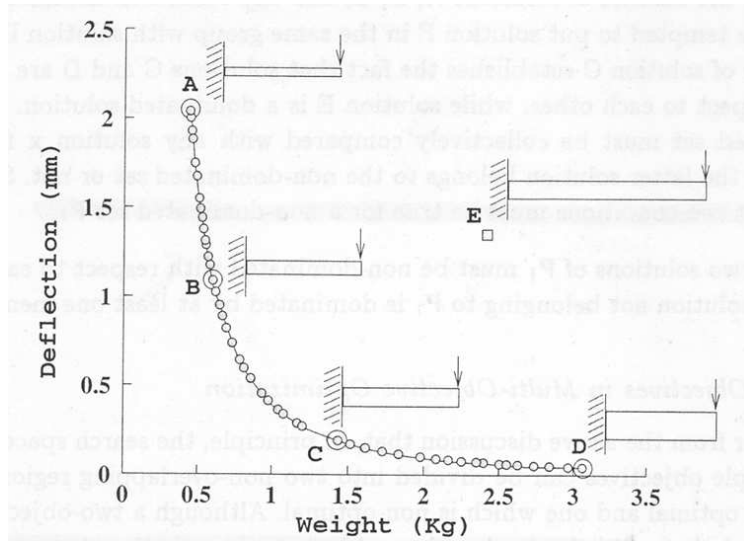
- f_1 : the end deflection δ (to be minimized),
- f_2 : the maximum developed stress in the beam σ_{max} (to be minimized).



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Dominance and Pareto-Optimal Solutions



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Domination: A solution $x^{(1)}$ is said to dominate another solution $x^{(2)}$, $x^{(1)} \preceq x^{(2)}$, if $x^{(1)}$ is not worse than $x^{(2)}$ in all objectives and $x^{(1)}$ is strictly better than $x^{(2)}$ in at least one objective.

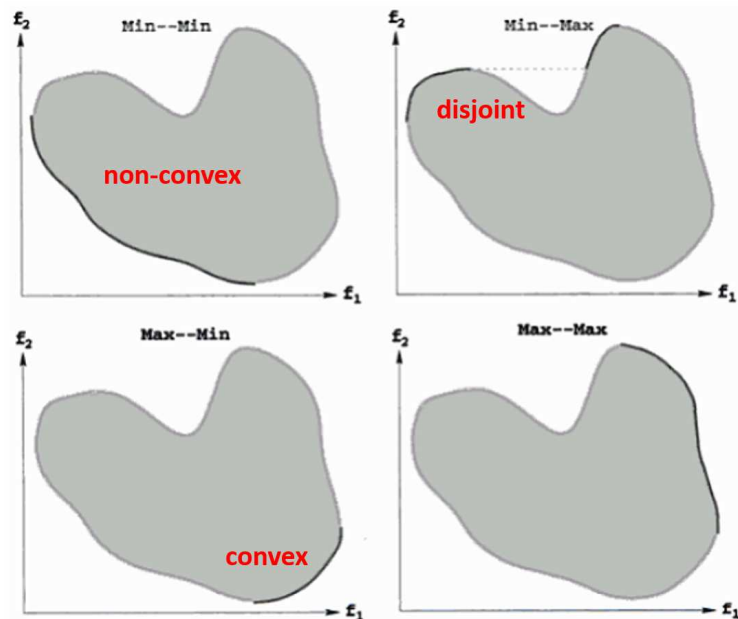
Solutions A, B, C, D are *non-dominated* solutions (Pareto-optimal solutions)

Solution E is *dominated* by C and B (E is non-optimal).

Properties of Dominance-Based Multi-Objective Optimization

Non-dominated set: Among a set of solutions P , the non-dominated set of solutions P' are those that are not dominated by any member of the set P .

Globally Pareto-optimal set is the non-dominated set of the entire feasible space.



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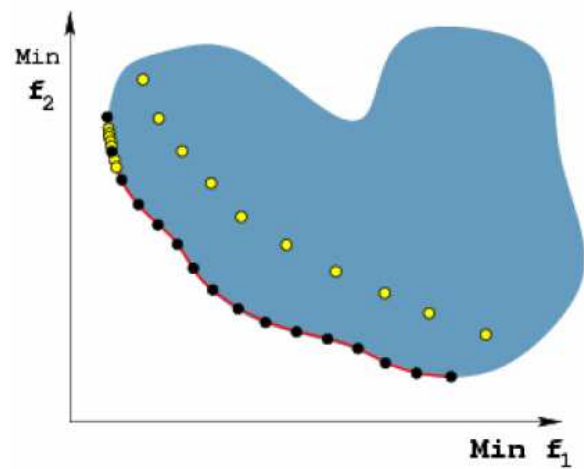
Goals of Dominance-Based Multi-Objective Optimization

Every finite set of solutions P can be divided into two non-overlapping sets:

- **non-dominated set** P_1 : contains all solutions that do not dominate each other
- **dominated set** P_2 : any solution from P_2 is dominated by at least one solution from P_1

In the absence of other factors (e.g. preference for certain objectives, or for a particular region of the tradeoff surface) there are **two goals of multi-objective optimization**:

- **Quality**: Find a set of solutions as close as possible to the Pareto-optimal front.
- **Spread**: Find a set of non-dominated solutions as diverse as possible.



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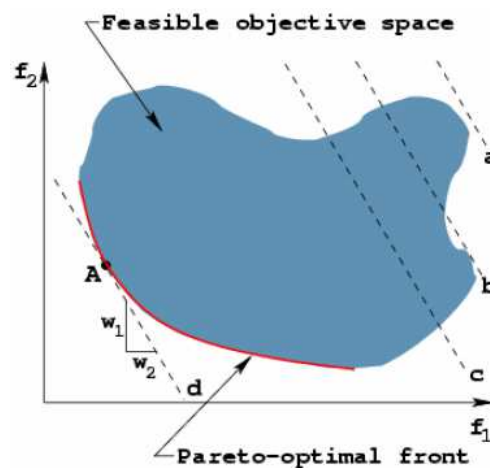
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Classical Approaches: Weighted Sum Method

- Construct a weighted sum of objectives and optimize

$$F(x) = \sum_{i=1}^m w_i \cdot f_i(x).$$

- User supplies weight vector w .
- Selection of weights w defines the slope of the line, which in turn determines the particular solution(s) on the boundary of the feasible space.

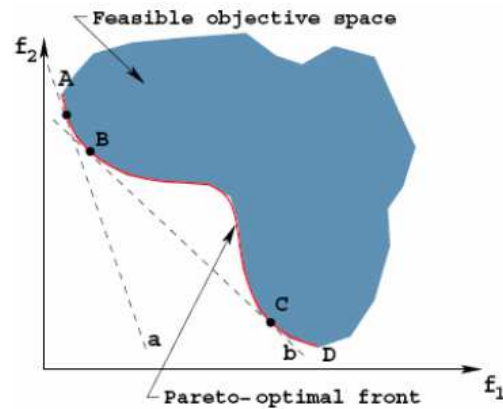


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Difficulties with Weighted Sum Method

- Need to know weight vector w .
- To find a set of trade-off solutions, the method must be run many times with varying w .
- Non-uniformity in Pareto-optimal solutions.
- Inability to find some Pareto-optimal solutions (in non-convex region).
- However, a solution of this approach is always Pareto-optimal.



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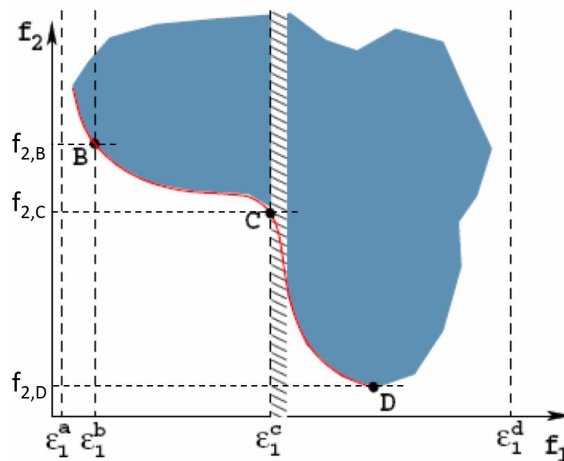
Classical Approaches: ϵ -Constraint Method

Method: Minimize a primary objective while expressing all the other objectives in the form of inequality constraints

$$\begin{aligned} &\text{minimize } f_p(x) \\ &\text{subject to } f_i(x) \leq \epsilon_i, \text{ for } i = 1, \dots, m, i \neq p. \end{aligned}$$

Example:

$$\begin{aligned} &\text{minimize } f_2(x) \\ &\text{subject to } f_1(x) \leq \epsilon_1. \end{aligned}$$



Remarks:

- To find a whole set of trade-off solutions, the method must be run many times.
- Need to know relevant ϵ vectors to ensure a feasible solution.
- Non-uniformity in Pareto-optimal solutions.
- However, any Pareto-optimal solution can be found with this method.

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Difficulties with Most Classical Approaches

- Need to run a single-objective optimizer many times.
- A lot of problem knowledge is required.
- Even then, good distribution of solutions is not guaranteed.
- Multi-objective optimization as an application of single-objective optimization.

Multi-objective EAs

Why and How Use EAs for Multi-Objective Optimization?

Why?

- *Population approach* suits well to find multiple solutions.
- *Niche-preservation methods* can be exploited to find diverse solutions.
- *Implicit parallelism* helps provide a parallel search.
Multiple applications of classical methods do not constitute a parallel search.

How?

- Modify the *fitness computation*.
- Emphasize non-dominated solutions for *convergence*.
- Emphasize unique solutions for *diversity*.

Multi-Objective Evolutionary Algorithms

■ Pareto Archived Evolution Strategy (PAES)

Knowles, J.D., Corne, D.W. (2000) Approximating the nondominated front using the Pareto archived evolution strategy. *Evolutionary Computation*, 8(2), pp. 149-172

■ Multiple Objective Genetic Algorithm (MOGA)

Carlos M. Fonseca, Peter J. Fleming: Genetic Algorithms for Multiobjective Optimization: Formulation, Discussion and Generalization, In Genetic Algorithms: Proceedings of the Fifth International Conference, 1993

■ Niche-Pareto Genetic Algorithm (NPGA)

Jeffrey Horn, Nicholas Nafpliotis, David E. Goldberg: A Niche Pareto Genetic Algorithm for Multiobjective Optimization, Proceedings of the First IEEE Conference on Evolutionary Computation, IEEE World Congress on Computational Intelligence, 1994

■ SPEA2

Zitzler, E., Laumanns, M., Thiele, L.: SPEA2: Improving the Strength Pareto Evolutionary Algorithm For Multiobjective Optimization, In: Evolutionary Methods for Design, Optimisation, and Control, Barcelona, Spain, pp. 19-26, 2002

■ NSGA

Srinivas, N., and Deb, K.: Multi-objective function optimization using non-dominated sorting genetic algorithms, *Evolutionary Computation Journal* 2(3), pp. 221-248, 1994

■ NSGA-II

Kalyanmoy Deb, Samir Agrawal, Amrit Pratap, and T Meyarivan: A Fast Elitist Non-Dominated Sorting Genetic Algorithm for Multi-Objective Optimization: NSGA-II, In Proceedings of the Parallel Problem Solving from Nature VI Conference, 2000

■ ...

Non-Dominated Sorting Genetic Algorithm (NSGA)

Common features with the standard GA:

- variation operators – crossover and mutation,
- selection method – Stochastic Remainder Roulette-Wheel,
- standard generational evolutionary model.

Differences of NSGA from SGA:

- fitness assignment scheme which *prefers non-dominated solutions*, and
- fitness sharing strategy which *preserves diversity among solutions of each non-dominated front*.

NSGA steps:

1. Initialize population of solutions.
2. Repeat
 - Calculate objective values and assign fitness values.
 - Generate new population.

Until stopping condition is fulfilled.

Fitness Sharing

Diversity preservation method originally proposed for solving multi-modal optimization problems so that GA is able to discover and evenly sample all optima.

Idea: decrease fitness of similar solutions

Algorithm to calculate the shared fitness value of i -th individual in population of size N

1. Calculate the distances d_{ij} of individual i to all individuals j .
2. Calculate values of *sharing function* between individual i and all individuals j :

$$Sh(d_{ij}) = \begin{cases} 1 - \left(\frac{d_{ij}}{\sigma_{share}}\right)^\alpha, & \text{if } d_{ij} \leq \sigma_{share}, \\ 0, & \text{otherwise.} \end{cases}$$

3. Calculate *niche count* nc_i of individual i :

$$nc_i = \sum_{j=1}^N Sh(d_{ij})$$

4. Calculate *shared fitness* of individual i :

$$f'_i = f_i / nc_i$$

Remark: If $d = 0$, then $Sh(d) = 1$, meaning that two solutions are identical. If $d \geq \sigma_{share}$, then $Sh(d) = 0$ meaning that two solutions do not have any sharing effect on each other.

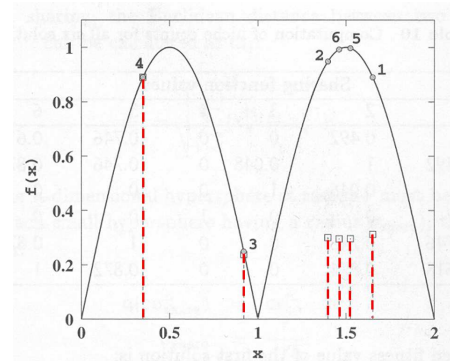
Fitness Sharing: Example

Bimodal function, six solutions, and corresponding shared fitness values.

- $\sigma_{share} = 0.5, \alpha = 1$.

Sol. i	String	Decoded value	$x^{(i)}$	f_i	nc_i	f'_i
1	110100	52	1.651	0.890	2.856	0.312
2	101100	44	1.397	0.948	3.160	0.300
3	011101	29	0.921	0.246	1.048	0.235
4	001011	11	0.349	0.890	1.000	0.890
5	110000	48	1.524	0.997	3.364	0.296
6	101110	46	1.460	0.992	3.364	0.295

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Let's take the first solution:

- $d_{11} = 0.0, d_{12} = 0.254, d_{13} = 0.731, d_{14} = 1.302, d_{15} = 0.127, d_{16} = 0.191$
- $Sh(d_{11}) = 1, Sh(d_{12}) = 0.492, Sh(d_{13}) = 0, Sh(d_{14}) = 0, Sh(d_{15}) = 0.746, Sh(d_{16}) = 0.618$.
- $nc_1 = 1 + 0.492 + 0 + 0 + 0.746 + 0.618 = 2.856$
- $f'(1) = f(1) / nc_1 = 0.890 / 2.856 = 0.312$

Remark:

- The above example computes d_{ij} in decision space, $d_{ij} = d(x_i - x_j)$.
- To create diverse set of non-dominated solutions, we have to compute it in the objective space, e.g., $d_{ij} = d(f(x_i) - f(x_j)) = d(z_i - z_j)$ (or see next slide).

NSGA: Fitness Assignment

Input: Set P of solutions with assigned objective values.

Output: Set of solutions with assigned fitness values (the bigger the better).

1. Choose sharing parameter σ_{share} , small positive number ϵ , initialize $f_{max} = PopSize$ and front counter $front = 1$
2. Find set $P' \subset P$ of non-dominated solutions.
3. For each $q \in P'$,
 - assign fitness $f(q) = f_{max}$,
 - calculate sharing function with all solutions in P' , niche count nc_q among solutions of P' only, the normalized Euclidean distance d_{ij} is calculated as

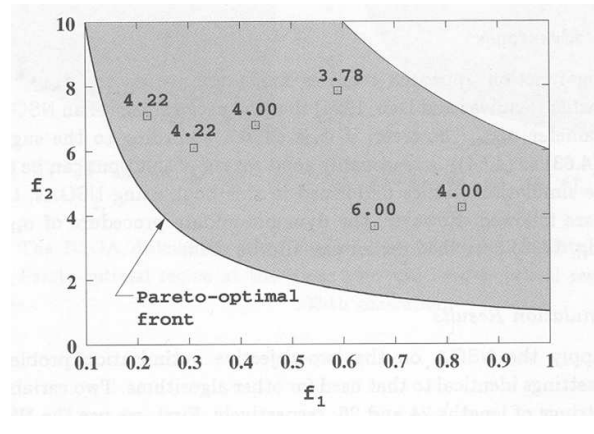
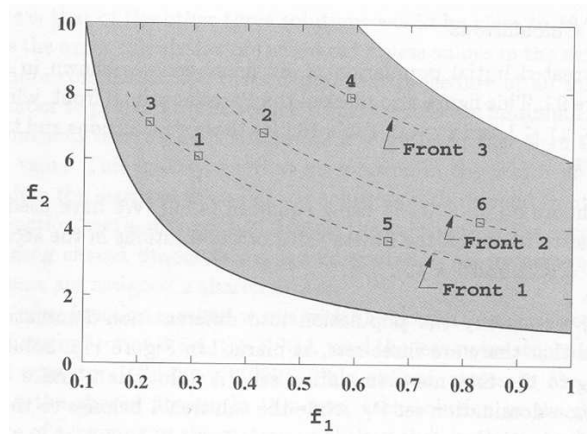
$$d_{ij} = \sqrt{\sum_{m=1}^M \left(\frac{f_m^{(i)} - f_m^{(j)}}{f_m^{max} - f_m^{min}} \right)^2},$$

- calculate shared fitness $f'(q) = f(q) / nc_q$.
4. $f_{max} = \min(f'(q) : q \in P') - \epsilon$,
 $P = P \setminus P'$,
 $front = front + 1$.
 5. If not all solutions are assessed go to step 2, otherwise stop.

NSGA: Fitness Assignment (cont.)

Example:

- First, 6 solutions are classified into different non-dominated fronts.
- Then, the fitness values are calculated according to the fitness sharing method.
 - The sharing function method is used front-wise.
 - Within a front, less dense solutions have better fitness values.



NSGA: Conclusions

Computational complexity

- Governed by the non-dominated sorting procedure and the sharing function implementation.
 - **non-dominated sorting** – complexity of $O(MN^3)$.
 - **sharing function** – requires every solution in a front to be compared with every other solution in the same front, total of $\sum_{j=1}^{\rho} |P_j|^2$, where ρ is a number of fronts.
Each distance computation requires evaluation of n differences between parameter values.
In the worst case, when $\rho = 1$, the overall complexity is of $O(nN^2)$.

Advantages:

- Assignment of fitness according to non-dominated sets makes the algorithm converge towards the Pareto-optimal region.
- Sharing allows phenotypically diverse solutions to emerge.

Disadvantages:

- non-elitist
- sensitive to the sharing method parameter σ_{share}
 - requires some guidelines for setting the σ_{share}
 - e.g., $\sigma_{share} = \frac{0.5}{\sqrt{q}}$ based on the expected number of optima q

NSGA-II

Fast non-dominated sorting approach

- Computational complexity is $O(MN^2)$.

Diversity preservation

- The sharing function method is replaced with a **crowded comparison approach**.
- Parameterless approach.

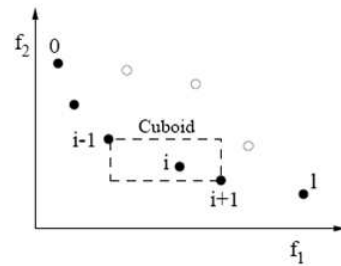
Elitist evolutionary model

- Only the best solutions survive to subsequent generations.

NSGA-II: Diversity preservation

Density estimation: **crowding distance** estimates how much unique the solution is.

- For individual i , find its predecessor and successor in each objective.
- Crowding distance $i^{distance}$ is the sum of differences in objective values of predecessor and successor across all objectives.
- For individuals with extreme value of at least one objective, $i^{distance} = \infty$.



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Crowded comparison operator \prec_c :

- Every solution in the population has two attributes:
 1. non-domination rank i^{rank} , and
 2. crowding distance $i^{distance}$
- A partial order \prec_c is defined as:

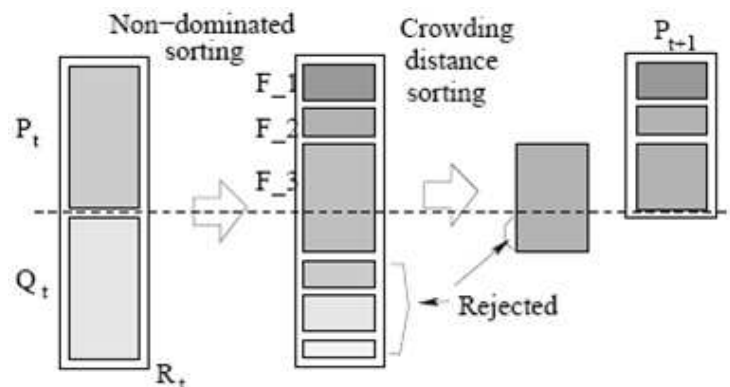
$$i \prec_c j \quad \text{if} \quad i^{rank} < j^{rank} \quad \text{or} \quad (i^{rank} = j^{rank} \quad \text{and} \quad i^{distance} > j^{distance}).$$

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NSGA-II: Evolutionary Model

1. Sort the current population P_t based on the non-domination. Each solution is assigned a fitness equal to its non-domination level (1 is the best).
2. Apply the usual binary tournament selection, recombination, and mutation to create a child population Q_t of size N.
3. Combine both populations: $R_t = P_t \cup Q_t$. (Steady-state algorithm, elitism is ensured.)
4. Perform replacement (environmental selection): Population P_{t+1} is formed according to the following schema



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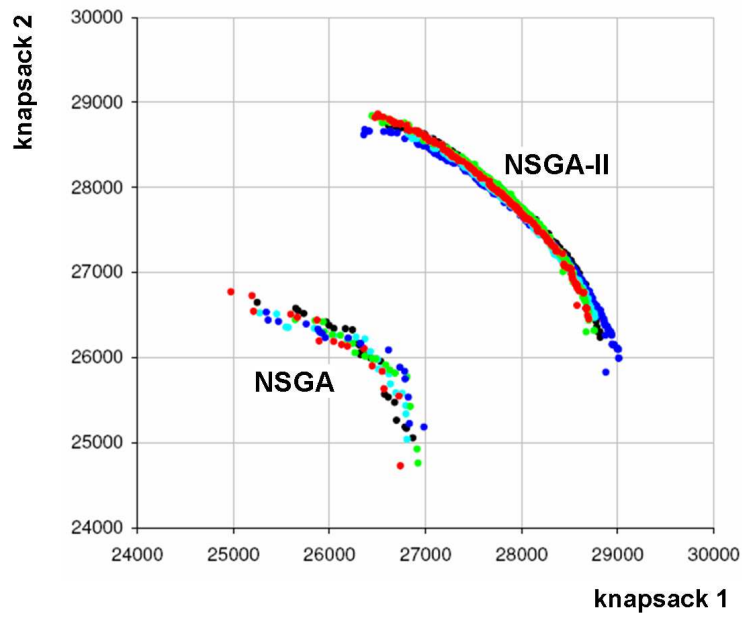
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Simulation Results: NSGA vs. NSGA-II

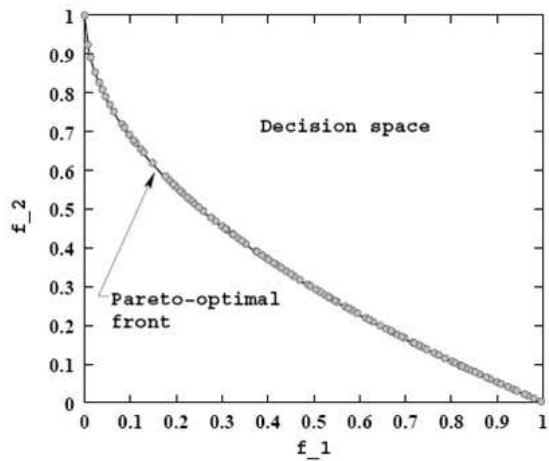
Comparison of NSGA and NSGA-II on bi-objective 0/1 Knapsack Problem with 750 items.

NSGA-II outperforms NSGA with respect to both performance measures.

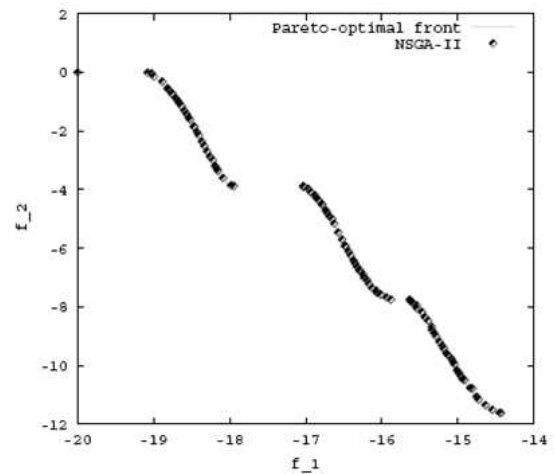


NSGA-II: Simulation Results on Various Types of Problems

Problem with continuous Pareto-optimal front



Problem with discontinuous Pareto-optimal front



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NSGA-II: Constraint Handling Approach

Binary tournament selection with modified domination concept is used to choose the better solution out of the two solutions i and j , randomly picked up from the population.

In the presence of constraints, each solution in the population can be either **feasible** or **infeasible**, so that there are the following three possible situations:

1. both solutions are feasible,
2. one is feasible and other is not,
3. both are infeasible.

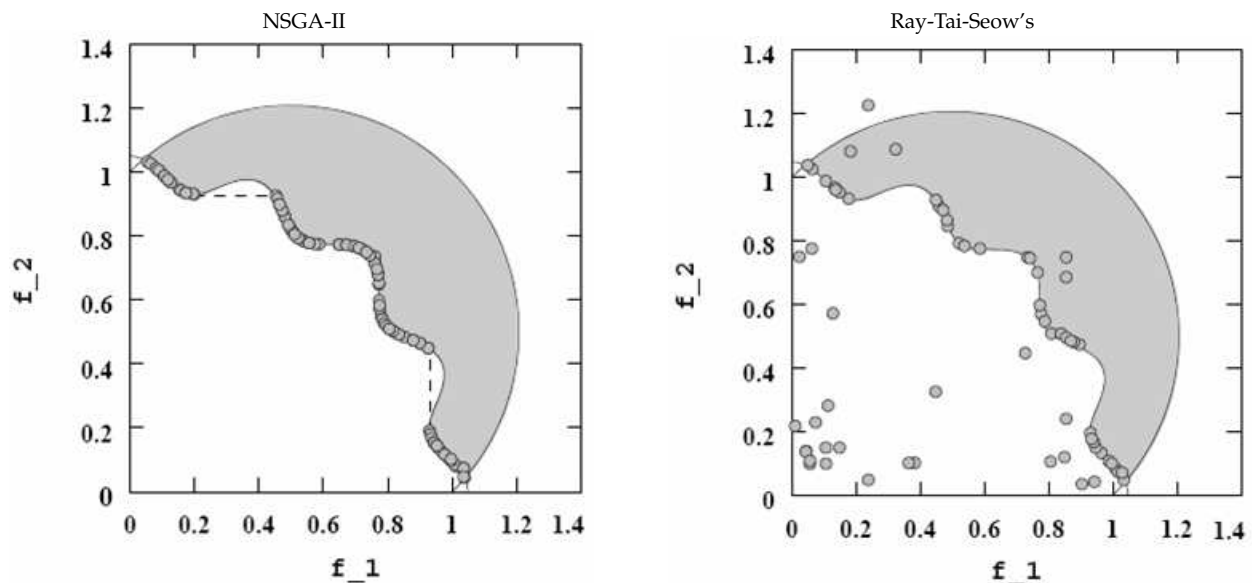
Constrained-domination: A solution i is said to constrained-dominate a solution j , if any of the following conditions is true:

1. Solution i is feasible and solution j is not.
2. Solutions i and j are both infeasible, but solution i has a smaller overall constraint violation.
3. Solutions i and j are feasible, and solution i dominates solution j .

NSGA-II: Simulation Results (cont.)

Comparison of NSGA-II and Ray-Tai-Seow's Constraint handling approach

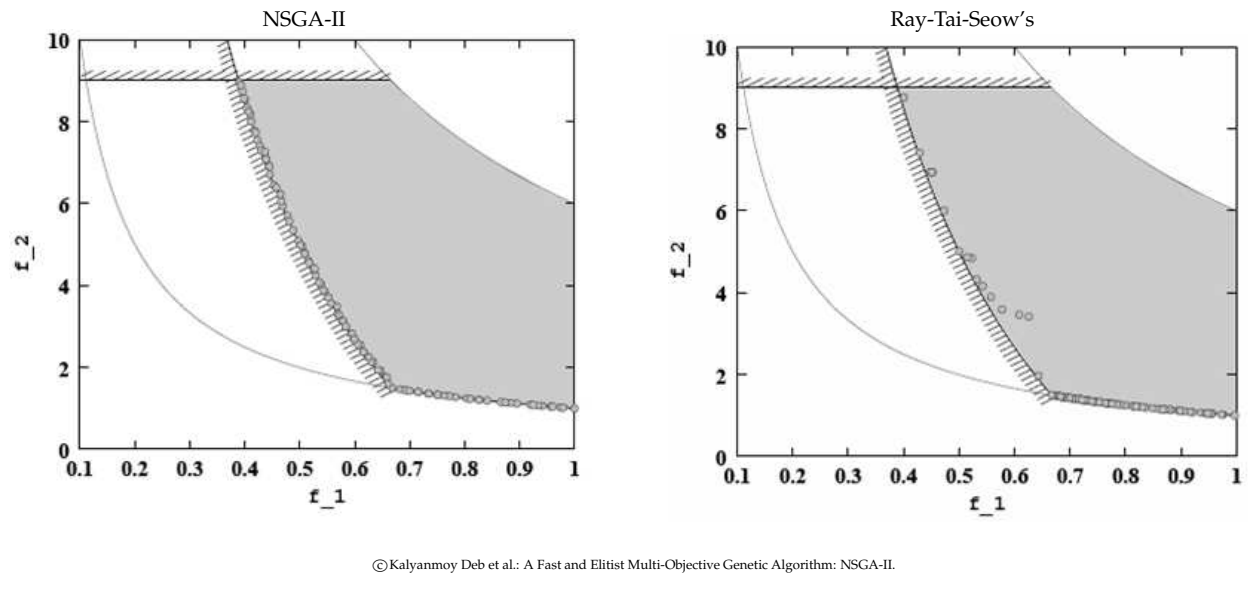
- Ray, T., Tai, K. and Seow, K.C. "Multiobjective Design Optimization by an Evolutionary Algorithm", Engineering Optimization, Vol.33, No.4, pp. 399-424, 2001.



© Kalyanmoy Deb et al.: A Fast and Elitist Multi-Objective Genetic Algorithm: NSGA-II.

NSGA-II: Simulation Results (cont.)

Comparison of NSGA-II and Ray-Tai-Seow's's Constraint handling approach:



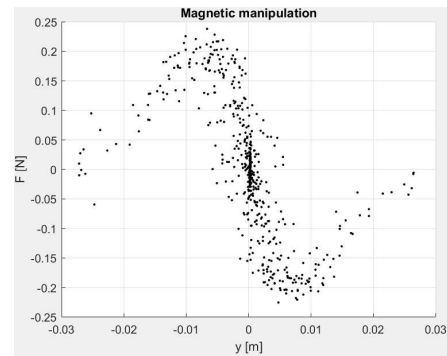
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NSGA-II: Bi-objective Symbolic Regression

Optimization objectives:

- Minimize MSE on the training data set.
- Minimize deviation of the symbolic models from the desired properties.



Desired properties:

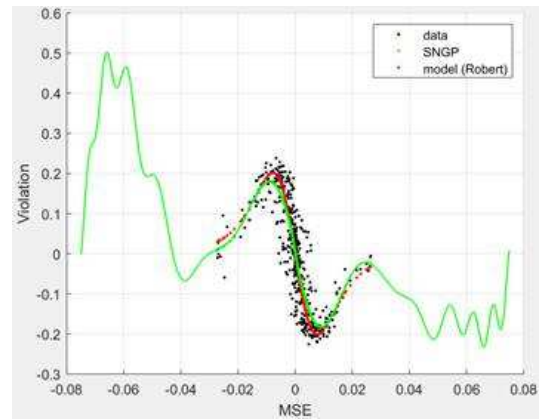
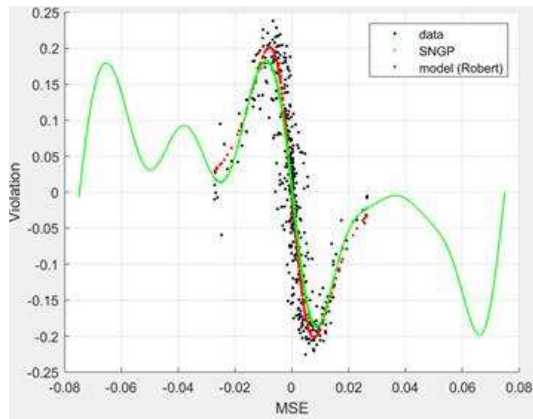
- Monotonically increasing in the intervals $y = \langle -0.075, -0.01 \rangle$ and $y = \langle 0.01, 0.075 \rangle$
- Monotonically decreasing in the interval $y = \langle -0.07, 0.07 \rangle$
- $F(y) \geq 0$, for $y \in \langle -0.075, 0.0 \rangle$
- $F(y) \leq 0$, for $y \in \langle 0.0, 0.075 \rangle$
- $|F(0.0)| < 0.005$
- $|F(-0.075) - 0.001| < 0.0005$
- $|F(0.075) + 0.001| < 0.0005$

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NSGA-II: Bi-objective Symbolic Regression

Well-fit models *w.r.t. the MSE on training data* only:

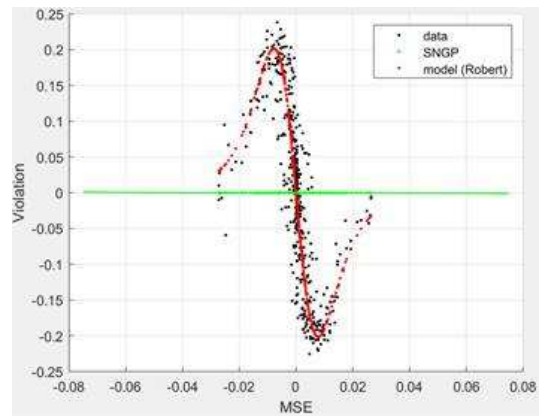
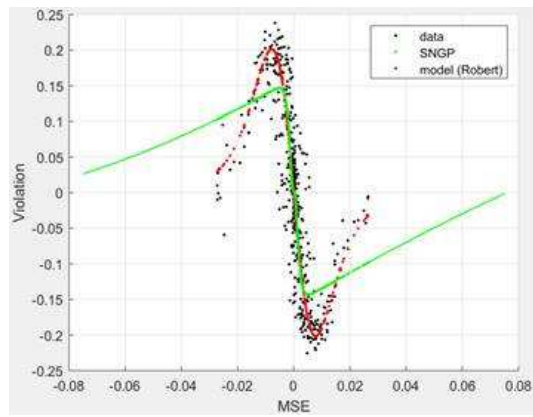


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NSGA-II: Bi-objective Symbolic Regression

Well-fit models *w.r.t. the constraint violations*:

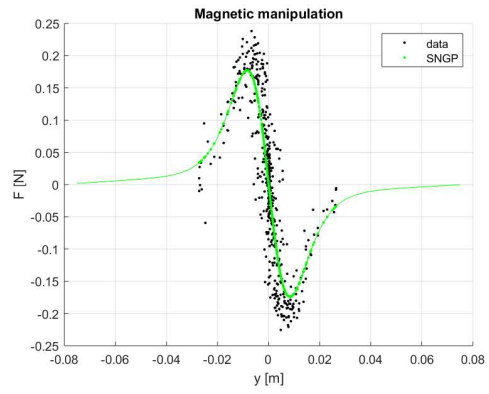
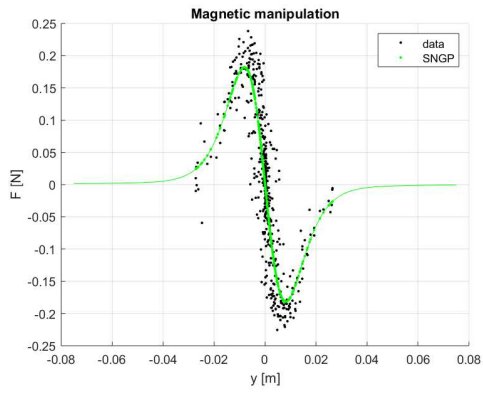


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NSGA-II: Bi-objective Symbolic Regression

Models with *small MSE on training data* that *fully comply with the constraints*:

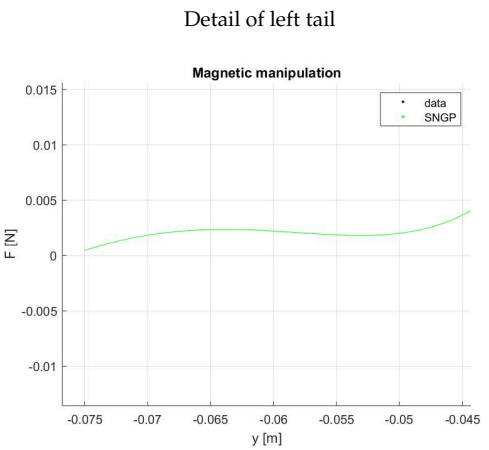
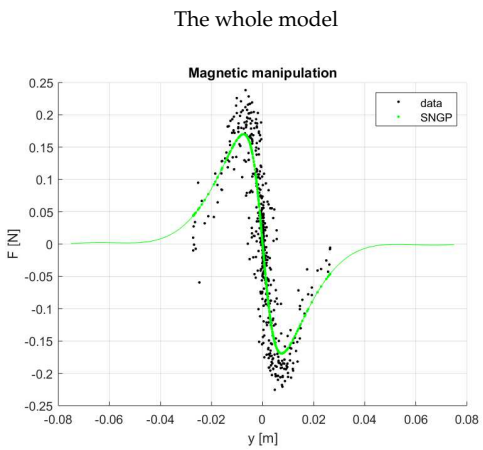


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NSGA-II: Bi-objective Symbolic Regression

Models with *small MSE on training data* that *almost fully comply with the constraints*:



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Strength Pareto Evolutionary Algorithm 2 (SPEA2)

SPEA2 maintains two sets of solutions:

- **regular population** of newly generated solutions, and
- **archive**, which contains a representation of the nondominated front among all solutions considered so far.

Archive:

- **The archive size is fixed**, i.e., whenever the number of nondominated individuals is less than the predefined archive size, the archive is filled up by *good* dominated individuals.
- A **truncation method** is invoked when the nondominated front exceeds the archive limit.
- A member of the archive is only removed if
 1. a solution has been found that dominates it, or
 2. the maximum archive size is exceeded and the portion of the front where the archive member is located is overcrowded.
- The archive makes it possible not to lose certain portions of the current nondominated front due to random effects.
- **All individuals in the archive participate in selection.**

SPEA2: Algorithm

Input: N is the population size, \bar{N} is the archive size.

1. **Initialization:** Generate an initial population P_0 and create the empty archive $\bar{P}_0 = \emptyset$. Set $t = 0$.
2. **Fitness assignment:** Calculate fitness of individuals in P_t and \bar{P}_t .
3. **Environmental selection:** Copy all nondominated individuals in P_t and \bar{P}_t to \bar{P}_{t+1} .
 - If size of \bar{P}_{t+1} exceeds \bar{N} then reduce \bar{P}_{t+1} using the truncation operator.
 - If size of \bar{P}_{t+1} is less than \bar{N} then fill \bar{P}_{t+1} with dominated solutions in P_t and \bar{P}_t .
4. **Termination:** If $t \geq T$ then return nondominated solutions in \bar{P}_{t+1} . Stop.
5. **Mating selection:** Perform binary tournament selection with replacement on \bar{P}_{t+1} in order to fill the mating pool.
6. **Variation:** Apply recombination and mutation operators to the mating pool and fill P_{t+1} with the generated solutions.
7. Increment generation counter $t = t + 1$.
8. Go to Step 2.

SPEA2: Fitness Assignment

Fitness assignment (fitness should be minimized):

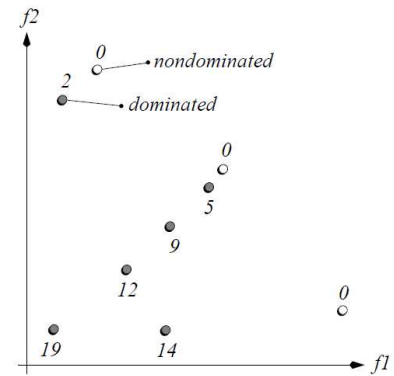
- For each individual, both dominating and dominated solutions are taken into account.
- Each individual i in the archive \bar{P}_t and in the population P_t is assigned a **strength value** $S(i)$, representing the number of solutions it dominates.
- The raw fitness $R(i)$ of an individual i is calculated as

$$R(i) = \sum_{j \in P_t + \bar{P}_t, j \succ i} S(j),$$

i.e., $R(i)$ is determined by the strengths of its dominators in both archive and population.

$R(i) = 0$ corresponds to a nondominated solution.

- Since the **raw fitness assignment** is based on the concept of Pareto dominance, it **may fail when most individuals do not dominate each other**.



Both objectives should be maximized.

SPEA2: Density Estimation

Density information is incorporated to discriminate between individuals having identical raw fitness values.

The density at any point is estimated as a (decreasing) function of the distance to the k -th nearest data point – calculated as the inverse of the distance to the k -th nearest neighbor.

- k equal to the square root of the sample size is used: $k = \sqrt{N + \bar{N}}$.
- **Density** $D(i)$ is calculated as

$$D(i) = \frac{1}{\sigma_i^k + 2}$$

where σ_i^k is the distance to the k -th nearest neighbor and it is made sure that $D(i) < 1$.

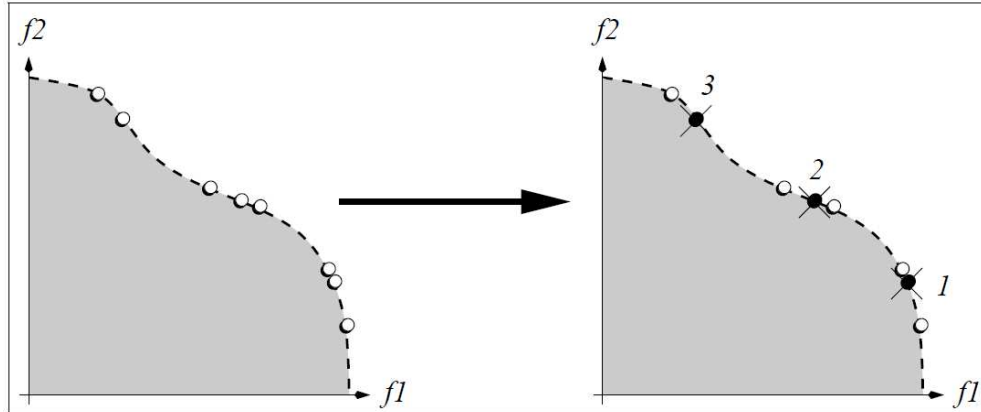
Final fitness is given as

$$F(i) = R(i) + D(i).$$

SPEA2: Environmental Selection

After copying all nondominated individuals from archive and population to the archive of the next generation,

- if the archive is too small (i.e. $|\bar{P}_{t+1}| < \bar{N}$), the best $\bar{N} - |\bar{P}_{t+1}|$ dominated solutions (w.r.t. fitness) in the previous archive and population are copied to the new archive;
- if the archive is too large (i.e. $|\bar{P}_{t+1}| > \bar{N}$), individuals from \bar{P}_{t+1} are iteratively removed until $|\bar{P}_{t+1}| = \bar{N}$. At each iteration, the individual which has the minimum distance to another individual is chosen (a tie is broken by considering the second smallest distances and so forth).



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SPEA2: Conclusions

SPEA2

- uses the concept of **Pareto dominance** in order to assign scalar fitness values to individuals;
- uses a **fine-grained fitness** assignment strategy which **incorporates density information** in order to distinguish between solutions that are indifferent, i.e., do not dominate each other;
- uses environmental selection in order to keep the optimal diversity in the archive;
- seems to have advantages over NSGA-II in higher dimensional objective spaces.

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MOEA Performance Measures

The result of a MOEA run is not a single scalar value, but a collection of vectors forming a non-dominated set.

- Comparing two MOEA algorithms requires comparing the non-dominated sets they produce.
- However, there is no straightforward way to compare different non-dominated sets.

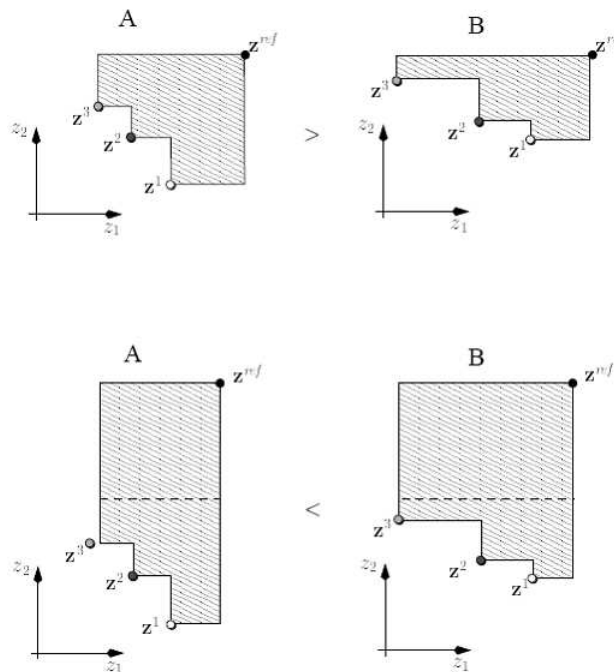
Three goals that can be identified and measured:

1. The distance of the resulting non-dominated front to the Pareto front should be minimized.
2. A good (in most cases uniform) distribution of the solutions found is desirable.
3. The extent of the obtained non-dominated front should be maximized, i.e., for each objective, a wide range of values should be present.

S Metric

Size of the space covered $S(X)$: it calculates the *hypervolume* of the multi-dimensional region enclosed by a set A and a *reference point* Z^{ref} . The hypervolume expresses the size of the region that is dominated by A .

So, the bigger the value of this measure the better the quality of A is, and vice versa.



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S Metric (cont.)

Pros:

- Given two non-dominated sets, A and B , if each point in B is dominated by a point in A then A will always be evaluated as being better than B .
- Independence: the hypervolume calculated for the given set is not dependent on any other, or any reference set.
- Differentiates between different degrees of complete outperformance of two sets.
- Intuitive meaning/interpretation.

Cons:

- Requires defining some upper boundary of the region.
This choice does affect the ordering of non-dominated sets.
- It has a large computational overhead, $O(n^{k+1})$, where n is the number of nondominated solutions and k is the number of objectives, rendering it unusable for many objectives or large sets.
- It multiplies apples by oranges, i.e., different objectives together.

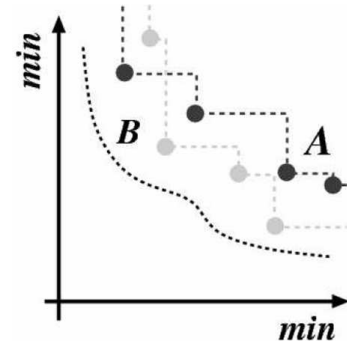
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C Metric

Coverage of two sets $C(X, Y)$: given two sets of non-dominated solutions X and Y found by the compared algorithms, the measure $C(X, Y)$ returns a ratio of a number of solutions of Y that are dominated by or equal to any solution of X to the whole set Y .

- It returns values from the interval $[0, 1]$.
- The value $C(X, Y) = 1$ means that all solutions in Y are covered by solutions of the set X . And vice versa, the value $C(X, Y) = 0$ means that none of the solutions in Y are covered by the set X .
- Always both orderings have to be considered, since $C(X, Y)$ is not necessarily equal to $1 - C(Y, X)$.



$$C(A, B) = 0.25, C(B, A) = 0.75$$

Properties:

- It has low computational overhead.
- If two sets are of different cardinality and/or the distributions of the sets are non-uniform, then it gives unreliable results.

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C Metric (cont.)

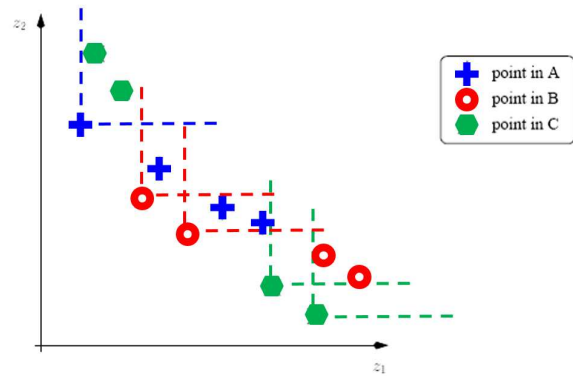
Properties:

- Any pair of C metric scores for a pair of sets A and B in which neither $C(A, B) = 1$ nor $C(B, A) = 1$, indicates that the two sets are incomparable according to the weak outperformance relation.
- It is cycleinducing – if three sets are compared using C , they may not be ordered.

Example:

- $C(A, B) = 0, C(B, A) = 3/4$
- $C(B, C) = 0, C(C, B) = 1/2$
- $C(A, C) = 1/2, C(C, A) = 0$

B considered better than A , A better than C , but C better than B .



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Summary

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Learning outcomes

After this lecture, a student shall be able to

- define a multi-objective optimization problem and describe the relationship between decision and objective spaces;
- define the dominance principle and the Pareto-optimal solutions;
- identify non-dominated solutions in a set of solutions;
- list and describe two goals of multi-objective optimization;
- describe some non-evolutionary approaches to multi-objective optimization and explain their deficiencies;
- implement evolutionary multi-objective algorithms and explain their differences from ordinary EA;
- explain algorithms NSGA, NSGA-II, SPEA2 and their differences;
- implement constraint handling in NSGA-II;
- define performance measures used in multi-objective optimizations (S metric and C metric);

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