Constraint-Handling in Evolutionary Algorithms

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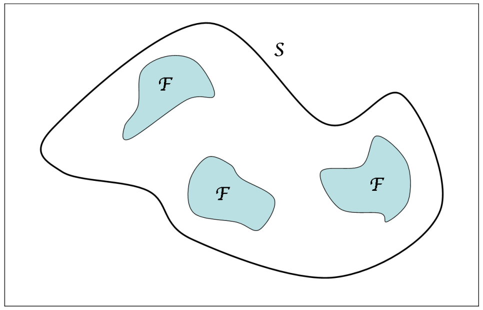
Substantial part of this material is based on slides for tutorial
'Constraint-Handling Techniques used with Evolutionary Algorithms'
presented at GECCO 2007 by Carlos A. Coello Coello.
See http://www.cs.york.ac.uk/rts/docs/GECCO_2007/docs/p3057.pdf

http://cw.felk.cvut.cz/doku.php/courses/a0m33eoa/start

Motivation

The general nonlinear programming problem (NLP) can be formulated as solving the objective function

$$\begin{array}{rll} \text{Minimize} & f(x), & x = [x_1, \ldots, x_n]^T; \\ \text{subject to} & g_i(x) \le 0, & i = 1, 2, ..., m; \\ & h_j(x) = 0, & j = 1, 2, ..., p; \end{array}$$



where

- x is a vector of n decision variables,
- each x_i, $i = 1, \ldots, n$ is bounded by lower and upper limits $x_i^{(L)} \le x_i \le x_i^{(U)}$, which define the search space $\mathcal{S}$,
- $\mathcal{F} \subseteq \mathcal{S}$ is the feasible region defined by m inequality and p equality constraints.

When solving NLP with EAs, equality constraints are usually transformed into inequality constraints of the form:

$$|h_j(x)| - \varepsilon \le 0$$

where ε is the tolerance allowed.

Standard Evolutionary Algorithm

```
Begin
   t=0
   Initialize P(t)
   Evaluate P(t)
   while (not termination-condition) do
   begin
     t=t+1
     Select P(t) from P(t-1)
     Recombine
     Evaluate P(t)
   end
End
```

Evolutionary Algorithms (EAs) have been found successful in solving a wide variety of optimization problems.

However, EAs are unconstrained search techniques. Therefore, it is necessary to incorporate constraints into components (mostly the fitness function) of the EA.

Taxonomy of Constraint-Handling Approaches

- Penalty functions.
- Special representations and operators.
- Repair algorithms.
- Multiobjective optimization techniques.

General Form of Fitness Function with Penalty Function

The idea of penalty functions is to **transform a constrained optimization problem into unconstrained one by adding certain value to the objective function** based on the amount of constraint violation present in the solution:

$$\psi(x) = f(x) + \sum_{i=1}^{m} r_i \times G_i + \sum_{j=1}^{p} r_j \times H_j$$

where $\psi(x)$ is the new objective function referred to as the **fitness function**, G_i and H_j are functions of the constraints violation $\big(g_i(x)$ and $h_j(x)\big)$, and r_i and r_j are positive constants called **penalty coefficients** or penalty factors.

A common form of G_i:

$$G_i = \text{max}(0, g_i(x))$$

A common form of H_j:

$$H_j = |h_j(x)|$$

or

$$H_j = \text{max}(0, g_j(x)), \text{ for } g_j \equiv |h_j(x)| - \varepsilon \leq 0$$

Types of Penalty Functions used with EAs

Two kinds of penalty functions w.r.t. to the search strategy they imply:

- **Exterior** – starting from an infeasible solution the search moves towards a feasible region.
- Interior – the penalty term is chosen such that its value will be small at points far away from the constraint boundaries and will tend to infinity as the constraint boundaries are approached.

  Starting from a feasible solution, the subsequent points will always lie within the feasible region.

  Constraint boundaries act as barriers preventing the search to leave the feasible region

  This seems nice, but represents a severe drawback indeed.

Four categories of penalty functions based on the way its parameters are being determined:

- Static penalty.
- Dynamic penalty.
- **Adaptive penalty**.
- Death penalty.

Static Penalty

Approaches in which the **penalty coefficients do not depend** on the current generation number, they remain constant during the entire evolution.

The approach proposed in [Homaifar94] defines levels of violation of the constraints (and penalty coefficients associated to them):

$$fitness(x) = f(x) + \sum_{i=1}^{m} (R_{k,i} \times (max[0, g_i(x)])^2)$$

where $R_{k,i}$ are the penalty coefficients used, m is the total number of constraints, $f(x)$ is the objective function, and $k = 1, 2, \ldots, l$, where l is the number of levels of violation defined by the user.

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Criticism:

- Penalty coefficients are difficult to generalize as they are, in general, problem-dependent.
- Presented method requires prior knowledge of the degree of constraint violation present in the problem (to define the levels of violation), which might not be easy to obtain in real-world applications.
- It is not a good idea to keep the same penalty coefficient along the entire evolution.

  The population evolves, so why should the coefficients that bias the search direction be static?

Dynamic Penalty

Penalty functions in which the **current generation number is involved in the computation of the corresponding penalty coefficients**.

Typically, the penalty coefficients are defined in such a way that **they increase over time** pushing the search towards the feasible region.

The approach from [Joines94] evaluates individuals as follows:

$$fitness(x) = f(x) + (C \times t)^{\alpha} \times SVC(\beta, x)$$

where C, α and β are user-defined constants; recommended values are $C = 0.5$, $\alpha = 1$ or 2, and $\beta = 1$ or 2.

$SVC(\beta, x)$ is defined as:

$$SVC(\beta, x) = \sum_{i=1}^{m} G_i^{\beta}(x) + \sum_{j=1}^{p} H_j(x)$$

where $G_i(x)$ and $H_j(x)$ are functions of the constraints violation ($g_i(x)$ and $h_j(x)$).

The dynamic penalty values increase as the evolution progresses through generations.

Dynamic Penalty: Criticism

- It is difficult to derive good dynamic penalty functions in practice.

  The presented approach is sensitive to changes in values of α, β and C and there are no guidelines for choosing proper values for particular problem.

- If a bad penalty coefficient is chosen, the EA may converge to either non-optimal feasible solutions (if the penalty is too high) or to infeasible solutions (if the penalty is too low).

Death Penalty

The **rejection of infeasible individuals** is probably the easiest way to handle constraints and it is also computationally efficient, because when a certain solution violates a constraint, it is rejected and generated again.

- The approach is to iterate, generating a new point at each iteration, until a feasible solution is found.

Thus, no further calculations are necessary to estimate the degree of infeasibility of such a solution.

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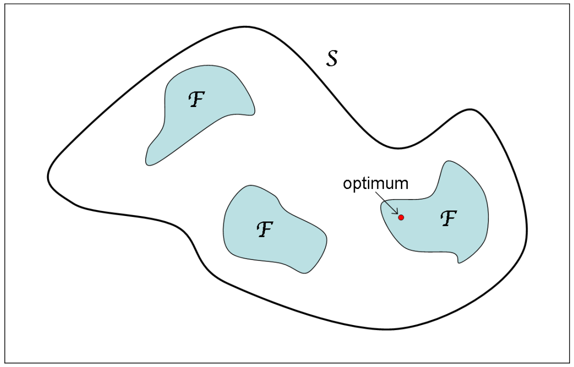
Criticism:

- Not advisable, except in the case of problems in which the proportion of feasible region in the whole search space is fairly large.
- No exploitation of the information from infeasible solutions.
- Search may "stagnate" in the presence of very small feasible regions.

Adaptive Penalty: Motivation

Let's assume the penalty fitness function of the following form:

$$\psi(x) = f(x) + r_g \times \sum_{i=1}^{m+p} G_i(x)^2$$



Deciding on an optimal (or near-optimal) value r_g is a difficult optimization problem itself.

- If r_g is too small, an infeasible solution may not be penalized enough. Hence, infeasible solutions may be evolved by an EA.
- If r_g is too large, a feasible solution is very likely to be found, but could be of very poor quality. A large r_g discourages the exploration of infeasible regions. This is inefficient for problems where feasible regions in the whole search space are disjoint and/or the constraint optimum lies close to the boundary of the feasible domain.

Reasonable exploration of infeasible regions may act as bridges connecting feasible regions.

How much exploration of infeasible regions ($r_g =?$) is reasonable?

- It is problem dependent.
- Even for the same problem, different stages of evol. search may require different r_g values.

Adaptive Penalty

- Self-Adaptive Fitness Formulation.
- Adaptive Segregational Constraint Handling EA (ASCHEA).
- Stochastic Ranking.

Self-Adaptive Fitness Formulation

This approach [Farmani03] uses an adaptive penalty that is applied in three steps:

1. The sum of normalized constrained violation is computed for each individual.
2. The best and worst solutions in the current population are identified.
3. Two-part penalty function is applied to the infeasible solutions.
   (a) The first part ensures that the worst of the infeasible solutions has a penalized objective function value higher or equal to the best solution in the population.
   (b) In the second part, the penalized objective function value of the worst of the infeasible solutions increases so that it is equal to that of the worst objective individual $\breve{x}$

Self-Adaptive Fitness Formulation: Step 1

The sum of normalized constrained violation is computed for each individual according to

$$i(x) = \frac{\sum_{1}^{m+p} \frac{c_j(x)}{c_{max,j}}}{m+p}$$

where $c_j(x)$ is a non-negative violation of constraint j and $c_{max,j}$ is the maximum value of the constraint j violation in the current population.

Such an infeasibility measure reflects both the number of active constraints and the magnitude of each constraint violation.

Self-Adaptive Fitness Formulation: Step 2

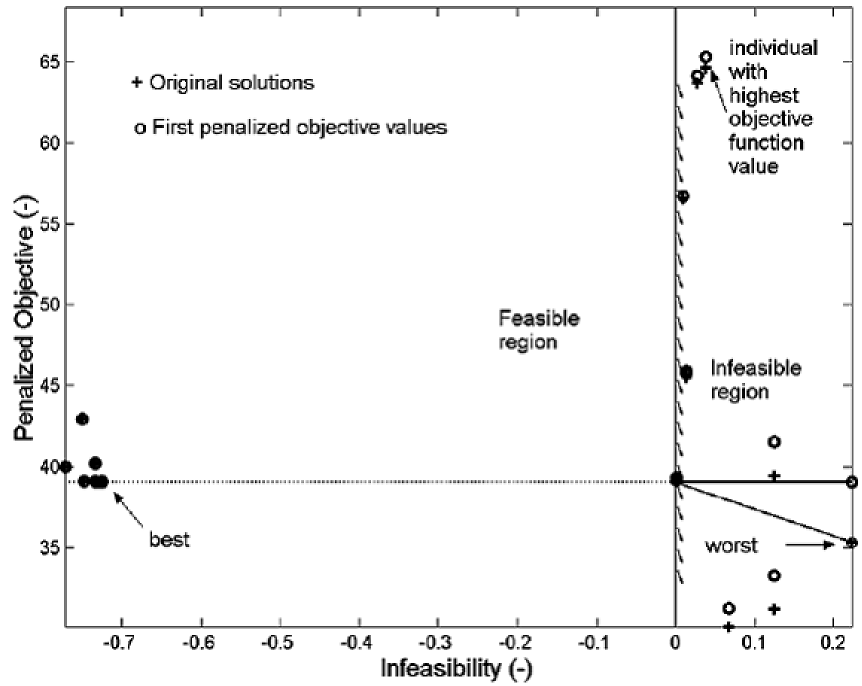
The penalty functions are applied in relation to three bounding solutions:

- Best individual $\breve{x}$.
  - If there is at least one feasible solution in the population then $\breve{x}$ is the feasible solution with the best objective value.
  - If all solutions are infeasible then $\breve{x}$ is the solution with the lowest infeasibility value (regardless of the objective function value).
- Worst of the infeasible solutions $\hat{x}$.
  - If there are some infeasible solutions having an objective function value lower than the $\breve{x}$ solution then $\hat{x}$ is the infeasible solution with the highest infeasibility value and objective function value lower than the $\breve{x}$ (ties are broken by minimizing the objective function value).
  - If all infeasible solutions have an objective function value greater than the $\breve{x}$ then the $\hat{x}$ is the infeasible solution with the highest infeasibility value. (ties are broken by maximizing the objective function value).
- Solution with the highest objective function value $\breve{x}$.

Self-Adaptive Fitness Formulation: Step 3

The first stage only applies if one or more infeasible solutions have a lower objective function value than the best solution $\breve{x}$

- The penalty is applied to all of the infeasible solutions.
- The goal is to increase the objective function value of the infeasible solutions such that the worst of the infeasible solutions $\hat{x}$ has an objective value equal to that of the best solution $\breve{x}$.
- All other infeasible solutions are also penalized but by a lesser amount, depending on their infeasibility value.



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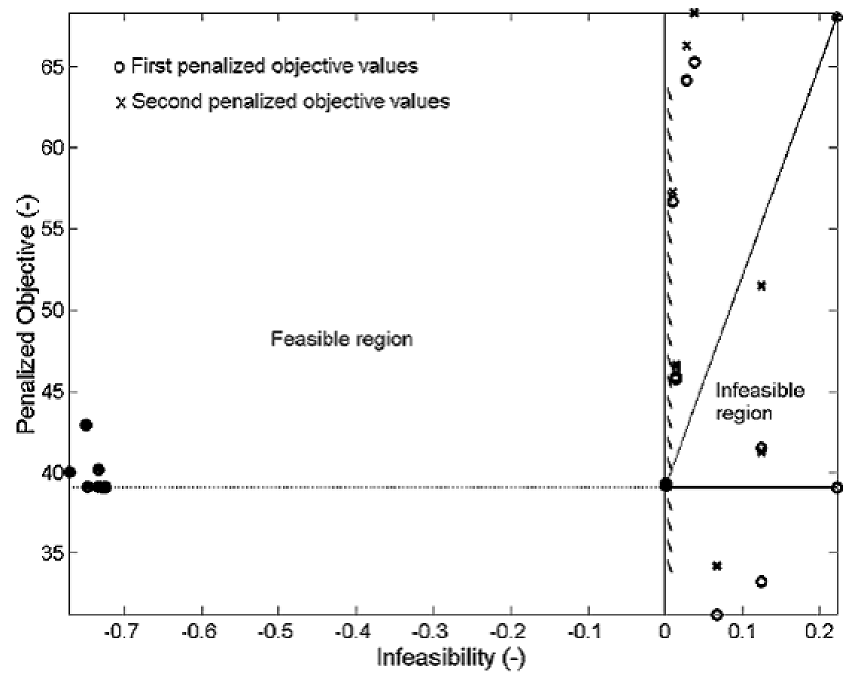
Self-Adaptive Fitness Formulation: Step 4

- The second penalty increases the objective function values such that the penalized objective function value of the worst infeasible individual $\hat{x}$ is equal to that of the worst objective individual $\breve{x}$.
- The penalty is realized by an exponential function which gives exponentially lower penalty to solutions with low infeasibility value, thus penalizing only slightly the infeasible solutions violate the constraints only a little.



Self-Adaptive Fitness Formulation: Conclusions

- The penalty factor is defined in terms of both the best and worst solutions.
- **Slightly infeasible solutions** (in the context of the current population) with good objective function value **remain fit**.
- Does not require any extra user-defined parameters. Does not require any parameter tuning.
- It is able to find the global optimum starting with a completely infeasible population of solution.
- It is easy to implement.

Adaptive Segregational Constraint Handling EA - ASCHEA

The main idea in ASCHEA [Hamida00] is to maintain both feasible and infeasible individuals in the population, at least when it seems necessary.

It proposes adaptive mechanisms at the population level for constraint optimization based on three main components:

1. An adaptive penalty function – takes care of the penalty coefficients according to the proportion of feasible individuals in the current population.
2. A constraint-driven mate selection – used to mate feasible individuals with infeasible ones and thus explore the region around the boundary of the feasible domain.
3. A so-called segregational replacement strategy – used to favor a given number of feasible individuals in the population.

ASCHEA: Adaptive Penalty

Let's assume the penalty function of the following form:

$$penal(x) = \alpha \sum_{i=1}^{m+p} G_i(x)$$

The penalty coefficient α is adapted based on the desired proportion of feasible solutions in the population τ_{target} and the current proportion at generation t τ_t:

$$\begin{array}{rl} \text{if}(\tau_t > \tau_{target}) & \alpha(t+1) = \alpha(t)/fact \\ \text{otherwise} & \alpha(t+1) = \alpha(t) * fact \end{array}$$

where $fact > 1$ is a user-defined parameter, a recommended value is around 1.1.

A recommended value of τ_{target} is around 0.6.

ASCHEA: Constraint-driven Mate Selection

Selection mechanism chooses the mate of feasible individuals to be infeasible.

- Only applied when too few (w.r.t τ_{target}) feasible individuals are present in the population.

More precisely, to select the mate x_2 for a first parent x_1:

if($0 < \tau_t < \tau_{target}$)and($x_1$ is feasible)	select x_2 among infeasible solutions only
otherwise	select x_2 according to fitness

ASCHEA: Segregational Replacement

Deterministic replacement mechanism used in ES-like scheme that should further enhance the chances of survival of feasible individuals.

Assume a population of μ parents, from which λ offspring are generated. Depending on the replacement scheme

- μ individuals out of λ offspring in case of the (μ, λ)-ES, or
- μ individuals out of λ offspring plus μ parents in case of the $(\mu + \lambda)$-ES

are selected to the new population in the following way:

1. First, feasible solutions are selected without replacement based on their fitness, until $\tau_{select} * \mu$ have been selected, or no more feasible solution is available.
2. The population is then filled in using standard deterministic selection on the remaining individuals, based on the penalized fitness.

Thus, a user-defined proportion of τ_{select} feasible solutions is considered superior to all infeasible solutions.

A recommended value of τ_{select} is around 0.3.

ASCHEA: Conclusions

- Feasibility elitism – as soon as a feasible individual appears, it can only disappear from the population by being replaced by a better feasible solution, even if the penalty coefficient reaches very small value.
- Constraint-driven mate selection accelerates the movement toward the feasible region of infeasible individuals, and helps to explore the region close to the boundary of the feasible domain.
- Adaptability – the penalty adaptation as well as the constraint-driven mate selection are activated based on the actual proportion of feasible solutions in the population.

Stochastic Ranking: What Penalty Methods Do?

Let's assume the penalty fitness function of the following form:

$$\psi(x) = f(x) + r_g \times \sum_{i=1}^{m+p} G_i(x)^2$$

For a given penalty $r_g > 0$, let the ranking of λ individuals be

$$\psi(x_1) \leq \psi(x_2) \leq \cdots \leq \psi(x_\lambda), \quad (1)$$

For any given adjacent pair i and $i+1$ in the ranked order

$$f_i + r_g G_i \leq f_{i+1} + r_g G_{i+1} \text{ where } f_i = f(x_i) \text{ and } G_i = G(x_i) \quad (2)$$

we define so called critical penalty coefficient

$$\check{r}_i = (f_{i+1} - f_i)/(G_i - G_{i+1}) \text{ for } G_i \neq G_{i+1} \quad (3)$$

Stochastic Ranking: What Penalty Methods Do?

For given choice of $r_g \geq 0$, there are three different cases which may give rise to inequality (2):

1. $f_i \leq f_{i+1}$ and $G_i \geq G_{i+1}$: Objective function plays a dominant role in determining the inequality and the value of r_g should be $0 < r_g < \check{r}_i$.
2. $f_i \geq f_{i+1}$ and $G_i < G_{i+1}$: Penalty function plays a dominant role in determining the inequality and the value of r_g should be $0 < \check{r}_i < r_g$.
3. $f_i < f_{i+1}$ and $G_i < G_{i+1}$: The comparison is nondominated and $\check{r}_i < 0$. Neither the objective nor the penalty function can determine the inequality by itself.

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   Ex.:

   $$\begin{array}{lll} f_i = 10, & G_i = 7 & \\ f_{i+1} = 20, & G_{i+1} = 5 & \\ \check{r}_i = (20-10)/(7-5) = 5 & \Longrightarrow & 0 < r_g < 5 \\ \hline r_g = 4: & 38 \leq 40 & \text{the inequality (2) holds} \\ r_g = 6: & 52 \not\leq 50 & \text{the inequality (2) does not hold} \end{array}$$

2. $f_i \geq f_{i+1}$ and $G_i < G_{i+1}$: Penalty function plays a dominant role in determining the inequality and the value of r_g should be $0 < \check{r}_i < r_g$.

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   Ex.:

   $$\begin{array}{lll} f_i = 20, & G_i = 5 & \\ f_{i+1} = 10, & G_{i+1} = 7 & \\ \check{r}_i = (10-20)/(5-7) = 5 \quad \Longrightarrow \quad 5 < r_g & & \\ \hline r_g = 4: & 40 \not\leq 38 & \text{the inequality (2) does not hold} \\ r_g = 6: & 50 \leq 52 & \text{the inequality (2) holds} \end{array}$$

3. $f_i < f_{i+1}$ and $G_i < G_{i+1}$: The comparison is nondominated and $\check{r}_i < 0$. Neither the objective nor the penalty function can determine the inequality by itself.

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   Ex.:

$$
\begin{aligned}
&f_i = 10, \quad G_i = 5 \\
&f_{i+1} = 20, \quad G_{i+1} = 7 \\
&\check{r}_i = (20 - 10)/(5 - 7) = -5 \quad \Longrightarrow \text{the inequality (2) holds for all } r_g > 0
\end{aligned}
$$

Stochastic Ranking: What Penalty Methods Do?

The value of r_g has no impact on the inequality (2) when nondominant and feasible individuals are compared.

The value of r_g is critical in the first two cases. It has to be within a certain range $\underline{r}_g < r_g < \overline{r}_g$

1. $\underline{r}_g$ is the minimum critical penalty coefficient computed from adjacent individuals ranked only according to the objective function.
2. $\overline{r}_g$ is the maximum critical penalty coefficient computed from adjacent individuals ranked only according to the penalty function.

Both bounds are problem dependent and may vary from generation to generation.

There are three categories of r_g values

1. $r_g < \underline{r}_g$: *Underpenalization* – All comparisons are based only on the fitness function.
2. $r_g > \overline{r}_g$: *Overpenalization* – All comparisons are based only on the penalty function.
3. $\underline{r}_g < r_g < \overline{r}_g$: All comparisons are based on a combination of objective and penalty functions.

   This is what a good constraint-handling technique should do – to balance between preserving feasible individuals and rejecting infeasible ones.

   But the optimal r_g is hard to determine.

Stochastic Ranking: Realization

This approach [Runarsson00] consists of an evolutionary algorithm that uses a penalty function and a rank-based selection.

- The idea of this approach is that **the balance between objective and penalty functions is achieved directly and explicitly**.
- It does not require the definition of a penalty coefficient r_g.

  Instead, it requires a **user-defined parameter P_f, which determines the balance** between the objective function and the penalty function.

Rank-based selection

- The population is sorted using an algorithm similar to bubble-sort.
- Parameter P_f specifies a probability of using only the objective function for comparisons of infeasible solutions.

  If both individuals are feasible then the probability of comparing them according to the objective function is 1.

  Otherwise, it is P_f.

  The reminder of the comparisons are realized based on the sum of constraint violation.

  Recommended range of P_f values is $(0.4, 0.5)$

Stochastic Ranking: Bubble-sort-like Procedure

```
I_j = j ∀ j ∈ {1, ... , λ}
for i = 1 to N do
    for j = 1 to λ − 1 do
        sample u ∈ U(0, 1)
        if (φ(I_j) = φ(I_{j+1}) = 0) or (u < P_f) then
            if (f(I_j) > f(I_{j+1})) then
                swap(I_j, I_{j+1})
            fi
        else
            if (φ(I_j) > φ(I_{j+1})) then
                swap(I_j, I_{j+1})
            fi
        fi
    od
    if no swap done break fi
```

Stochastic Ranking: Conclusions

- Does not use any specialized variation operators.
- Does not require a priori knowledge about a problem since it does not use any penalty coefficient r_g in a penalty function.
- The approach is easy to implement.

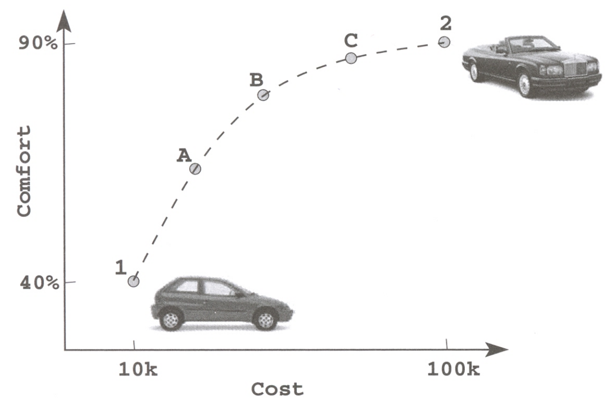
Approaches based on Evolutionary Multiobjective Optimization

General form of multi-objective optimization problem

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

- x is a vector of n decision variables: $x = (x_1, x_2, ..., x_n)^T$;
- g_j, h_k are inequality and equality constraints, respectively.
- **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).

  Motivation 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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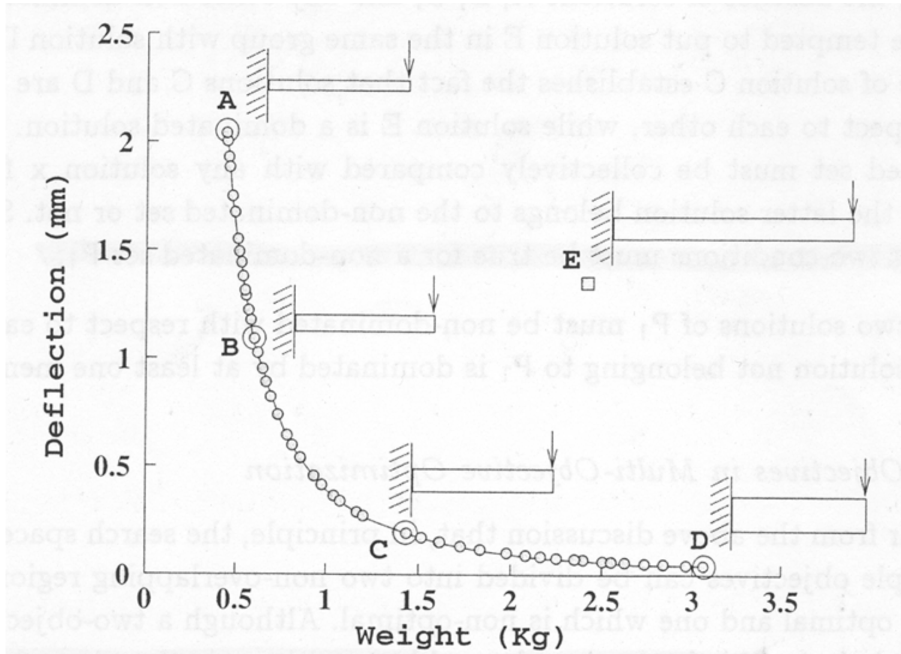
Multiobjective Techniques: Using Pareto Schemes



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Pareto dominance: *A solution $x^{(1)}$ is said to dominate the other solution $x^{(2)}$, $x^{(1)} \preceq x^{(2)}$, if $x^{(1)}$ is no 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).

Approaches based on Evolutionary Multiobjective Optimization

Two ways the NLP is transformed into a multiobjective optimization problem

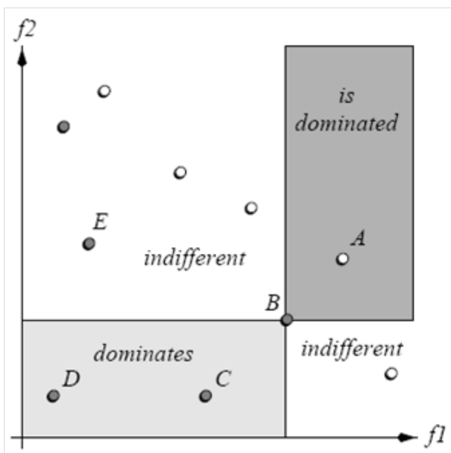
- NLP $\longrightarrow$ Unconstrained Bi-objective Optimization: Transforms the NLP into an unconstrained bi-objective optimization problem with the objectives being (1) the original objective function and (2) the sum of constraint violation.
- NLP $\longrightarrow$ Unconstrained Multiobjective optimization: Transforms the NLP into an unconstrained multiobjective optimization problem where the original objective function and each constraint are treated as separate objectives.

Bi-objective Optimization Techniques

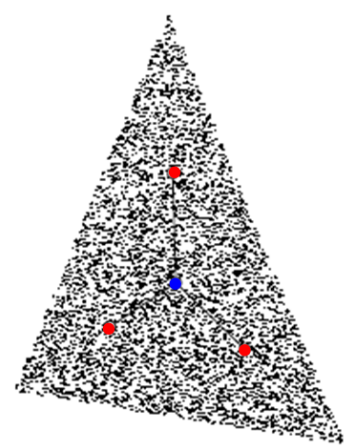
[Zhou03] – uses a **ranking procedure based on the Pareto strength** concept, i.e. counting the number of individuals which are dominated for a given solution.

- Ties are solved by the sum of constraint violation.
- Simplex crossover operator used to generate a set of offspring where
  - the solution with the highest Pareto strength and
  - the solution with the lowest constraint violation

  are both selected to take part in the population.



Strength concept



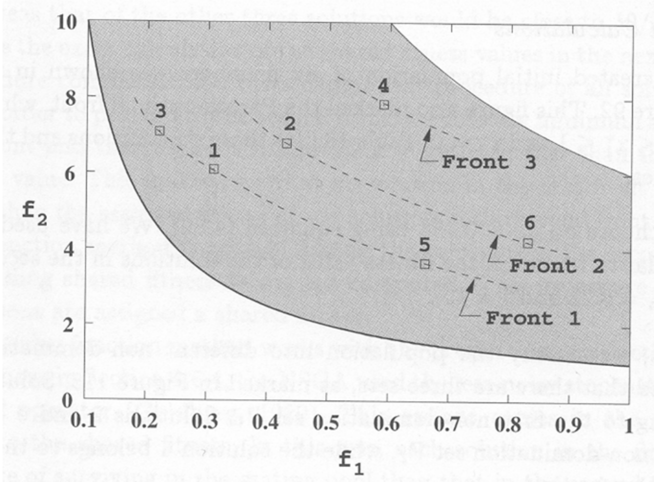
Simplex crossover

Bi-objective Optimization Techniques

[Venkatraman05] – approach divided in two phases:

1. The population is ranked based only on the sum of constraint violation – the goal is to find some feasible solutions.

1. Both objectives are taken into account.
   - Nondominated sorting is used to rank the population.
   - Niching scheme based on distance to the nearest neighbors is applied to promote a diversity of the population.



Disadvantage: The way the feasible region is approached is mostly at random because the quality is not considered in the first phase.

Multiobjective Techniques: Using Non-Pareto Schemes

[Coello00] – MOP approach based on VEGA's idea, where the population is divided into $m+1$ sub-populations, and each sub-population focuses on optimization of one objective.

- One sub-population handles the objective function of the problem and the individuals are selected based on the unconstrained objective function value.
- Each of the m remaining sub-populations takes one constraint as their fitness function.
- The aim is that each of the sub-populations tries to reach the feasible region corresponding to one individual constraint.

  By combining these sub-populations, the approach will reach the feasible region where all of the constraints are satisfied.

The main drawback is that the number of sub-population increases linearly with the number of constraints.

Multiobjective Techniques: NPGA-based Approach

[Coello02] – based on the Niched-Pareto Genetic Algorithm that uses binary tournament selection based on Pareto non-dominance.

- Parameter S_r, which indicates the minimum number of individuals that will be selected through dominance-based tournament selection.

  The remainder will be selected using a purely probabilistic approach. In other words, $(1 - S_r)$ individuals in the population are probabilistically selected.

  – Tournament selection – three possible situations when comparing two candidates
    1. Both are feasible. In this case, the candidate with a better fitness value wins.
    2. One is infeasible, and the other is feasible. The feasible candidate wins, regardless of its fitness function value.
    3. Both are infeasible – use a set of individuals to compare their dominance.
       (a) Check both candidates whether they are dominated by ind. from the comparison set.
       (b) If one is dominated by the comparison set, and the other is not dominated then the non-dominated candidate wins.
       Otherwise, the candidate with the lowest amount of constraint violation wins, regardless of its fitness function value.

  – Probabilistic selection – Each candidate has a probability of 50% of being selected.
- Robust, efficient and effective approach.

Multiobjective Techniques: Conclusions

- The most popular are the MOP approaches.
- The use of diversity mechanisms is found in most approaches.
- The use of explicit local search mechanisms is still scarce.

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